Three Essays on Bank Lending, Liquidity, and the Macroeconomy

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The Faculty of Economics, Business Administration and Information Technology of the University of Zurich hereby authorises the printing of this Doctoral Thesis, without thereby giving any opinion on the views contained therein.

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Introduction

The financial crisis 2007-2009, notwithstanding its detrimental effects for developed and emerging economies around the world, has been a blessing for academics working in the fields of Macro-Finance, the node and interaction between financial markets and the real economy. The relevance of financial markets for the macroeconomy has become apparent in full force, sparking a new wave of research in this area; away from models in which the state and soundness of capital and credit markets does not play any substantial role. While valuable and widely regarded attempts to build theoretical models, which are able to replicate some of the key causalities of the crisis[1], have been made, a major quantum leap for macroeconomic modeling is missing to this date.

As a quasi natural experiment, the crisis provides an opportunity to identify the most relevant links between financial markets and the macroeconomy by coherent display of the available data and formal identification of the key empirical relationships. This will provide guidance in determining the necessary ingredients to new macro-models, which, in turn, can allow deeper insights into the complex interactions at work.

The thesis presented here is aimed at contributing to the identification of central empirical relationships by analyzing the role of the banking sector and financial markets during the crisis.

While the complex developments in the financial sector have laid the ground for the cascade of dismal events after the collapse of Lehman Brothers on the 15th of September 2008, the main focus and fear of both central banks and governments has been the contraction in the supply of credit to the real economy. In this respect, the research on the Great Depression (first and foremost Bernanke (1983)), and its implications for the substantial effect of credit supply on real economy activity, has been influential in framing the mindset and actions of policy makers in the US, Europe, and many other countries.

Even though the increasing sophistication of credit markets in the last decades, materialized through the explosion in securitization activities, did cause a shift of

[1] See Brunnermeier (2009) and Mizen (2008) for a comprehensive illustration of the key factors and developments of the financial crisis 2007-2009.

business finance to debt instruments such as corporate bonds and commercial paper, the traditional bank loan still remains vital for many firms and individuals, that do not necessarily have access to funding from the capital markets. In fact, in most developed countries, small and medium sized businesses are creating a significant, if not the predominant, share of the jobs in the economy; and it is exactly them, which are highly dependent on bank loans as a source of funding for their investments and operations. At the same time, the increased complexity and globalization of financial markets had an influence on the structure and dynamics of the economies in the developed world.

Both politicians and the press have painted a picture of a serious shortage in the supply of credit to businesses and individuals in 2008/2009, despite the extensive and extraordinary measures taken by central banks and the unprecedented government rescue packages put in place to shore up banks' balance sheets.

Chapter 1 will get to the bottom of the most prominent claims held by the proponents of the "credit-crunch" theory. While it does not attempt to answer the question of whether there was a shortage in credit-supply or not, its purpose is to examine the validity of the most prominent arguments made for a "credit-crunch", which are mainly based on bank balance sheet weaknesses. In particular, a reduction in loans to small businesses, insufficient equity buffers, an over-reliance on capital market funding, liquidity shortages, and excessive risk taking are among the most frequently stated characteristics and causes of the alleged squeeze in banks' supply of funding. To sensibly address these points, bank-individual data from the quarterly *Reports of Condition and Income* (CALL reports) is employed, which provides extensive information on the balance sheet positions of all *Federal Deposit Insurance Corporation* (FDIC) member banks and savings institutions. Interestingly, convincing evidence can only be found for dangerously illiquid balance sheets and strongly increased risk taking, whereas a precipitation in small business lending, generally under-capitalized banks, and a heavy reliance on capital market funding, cannot be confirmed with the comprehensive dataset.

While Chapter 1 provides an important general insight, namely that liquidity shortages and heightened risk-taking are relevant catalysts, or even triggers, of the financial crisis 2007-2009, it does not examine which factors are actually driving the supply of credit.

Determining which factors are relevant for bank lending in the aggregate, however, requires a more formal approach, which is taken in Chapter 2. Individual banks' lending decisions are made on the basis of their balance sheet characteristics, given current and expected economic conditions. For example, the larger the equity buffer of a given bank, the greater is, *ceteris paribus*, its capacity to supply additional loans. An otherwise identical bank with a lower equity ratio is not as well insulated against possible credit defaults, and may also have higher costs of refinancing, given its higher probability of default. This, in turn, increases its marginal costs and makes it less willing to take on additional loans than the bank with the thicker equity cushion. Credit supply, however, is not directly observable; only lending is, which merely represents a, possibly constrained, equilibrium of supply and demand. Hence, any empirical analysis of credit supply determinants faces a fundamental identification problem, as *over time*, lending will also be influenced by credit demand. The literature has made progress on this issue by utilizing individual banks' balance sheet data. The idea is that at *one point in time*, banks with stronger balance sheets have a higher credit supply capacity, and therefore the cross-sectional variation in observed lending growth can identify how sensitive lending decisions are with respect to various balance sheet characteristics. Implicitly, it is assumed that bank-individual characteristics pin down credit supply decisions, whereas the factors driving demand are common to at least a group of banks (Gambacorta and Mistrulli (2004)). This literature, however, is primarily concerned with the effect of monetary policy on bank lending, called the bank lending channel. The effect of monetary policy on bank lending is then typically measured for an "average" bank.

Based on the econometric model introduced by Kashyap and Stein (2000) and the CALL report data mentioned above, the analysis in Chapter 2 goes further by introducing a consistent aggregation procedure over the cross-section, in order to derive a classification of the importance of a wide variety of balance sheet characteristics for the time-variation in *aggregate* lending - the taxonomy of bank balance sheet characteristics. The results indicate that aggregate lending of small banks is mainly driven by the sensitivity of lending with respect to three characteristics: 1. Core equity, which proved crucial for strong lending growth before and during the crisis; 2. The riskiness of its business model measured by the Basel I risk weight, suggesting a momentum in risk taking before Q3 2008; and 3. A common excess demand component. For the largest 5% of banks, the emerging picture looks quite different. The availability of capital market funding, proxied by the external financing ratio, was driving the largest part of large banks' lending decisions in the aggregate. As a next step, it is then analyzed in how far macroeconomic conditions can explain the changes in lending sensitivities over time. It appears that about half of the variation of small banks' lending sensitivities with respect to their core equity ratios and Basel I risk weights can be rationalized by improving and deteriorating expectations regarding future economic conditions, whereas macro-factors do not seem to explain a large part of large banks' aggregate lending dynamics. Two major implications for banking regulation can be drawn: Firstly, the new Basel III regulations seem capable to smooth lending dynamics over the business cycle and limit the momentum in risk-taking of small banks. Secondly, a close monitoring of large banks' non-equity and non-deposit financing activities would be advisable in order to assess potentially destabilizing effects of an excessive reliance on liquidity provision from financial markets.

As the approach in Chapter 2 is effectively based on individual banks' lending decisions, which are then aggregated up, the macroeconomic environment is taken as exogenous. The results are robust to the most probable feedback effect channels, yet, precisely the feedback effects from the financial sector to the real economy are of great interest on their own.

In Chapter 3, the real effects of financial market conditions and credit supply take center stage. During crisis times, the transmission mechanisms between financial markets and the real economy can be different than in normal times (Azariadis and Smith (1998)). Normal linear econometric models, however, do not capture conditional transmission mechanisms. To allow for potentially different dynamics under tranquil, as opposed to distressed, financial markets, I propose an endogenous Threshold-VAR (TVAR) model. It distinguishes between two different regimes, in which the parameters governing the dynamics of the system can be totally different. The two regimes are identified by a threshold, which itself is an endogenous variable. In this way, the TVAR model is general enough, not only to capture different transmission mechanisms *conditional* on endogenous variables like financial market conditions, but also to generate different impulse responses depending on the size and direction of structural shocks. The magnitude of the spread between interbank lending rates and US Treasury yields (TED spread) proxies the degree of distress in financial markets, and serves as the endogenous threshold in the model. The "normal" (low TED spread) regime and the "bad" (high TED spread) regime indeed exhibit distinctively different propagation mechanisms. Generally, the transmission mechanism of financial market conditions to the real economy is much more pronounced in the high TED spread regime. Non-linear Impulse Response and Variance Decomposition analysis further suggests, that a significant share of the real impact during the dot-com bubble in 1999-2000 and of the current financial crisis is due to adverse shocks to financial market conditions. Despite some evidence for a mutual feedback effect between financial market conditions and liquidity in regime 2, as suggested by Brunnermeier and Pedersen (2009), the feedback from liquidity shocks to financial market conditions and the real effects of liquidity shocks are small and short-lived. Even though the real effects of financial market conditions are significant, they are not accountable for more than one third of the variation in GDP growth. Financial market conditions hence can only explain a part of the observed variations in economic growth. As shocks to GDP growth itself explain most of the variation, changes in the expectation of future economic conditions are likely to be a relevant factor for the real dynamics observed in the run-up and during the recent financial crisis.

Chapter 1

Facts and Myths about Banking Sector Weaknesses in the US Before and During the Financial Crisis of 2007-2009 Evidence from CALL Reports

1.1 Introduction

The 2008/2009 financial crisis has been widely associated with an entailing "credit-crunch". Some authors, however, have argued that there is no clear evidence to support this view. While this paper will not provide new evidence for, or against, a shortage of credit-supply, its aim is to examine the most prominent arguments made for a "credit-crunch", which mainly hinge on bank balance sheet weaknesses. By analyzing the comprehensive and publicly available data from the *Reports of Condition and Income* (CALL reports), a much more detailed view on the validity of the central claims of the "credit-crunch" discussion is obtained, compared to previous analyses, which have mostly been based on aggregate data[1]. After reviewing some of the aggregate data from the *Flow of Funds* and pointing out their main implications and shortcomings, the following assertions are addressed:

1. Small banks, which did not receive direct government support, had to cut lending the most. As they are the most important providers of funding to small businesses, small businesses suffered a "credit crunch".

[1] See Chari et al. (2008)

2. Capital ratios were far too low. As a result, banks had to reduce their risky assets and had no capacity for granting loans to businesses.

3. Banks increasingly financed themselves through capital markets. Therefore, once investors stopped buying their debt securities, the ability of banks to refinance themselves was severely hindered and they simply did not have the necessary liquidity to supply loans to the real economy.

4. The fact that banks experienced problems when capital markets dried up, is due to the insufficient levels of cash and other liquid assets, which would have been needed to hedge the liquidity risks.

5. Banks exhibited excessive risk taking behavior, for the sake of maximizing their returns. Once the risks were materializing, the losses on their asset portfolios became so large, that banks were forced to cut down on lending to reduce risks.

The focus of the paper is on assessing the plausibility of the above claims, by inspecting the underlying statements regarding bank balance sheet weaknesses. Concretely, the respective claims are based on 1. a precipitation of small business loan supply, 2. low capital ratios, 3. an extraordinarily high degree of capital market financing, 4. insufficient liquidity buffers, and 5. excessive risk taking, respectively.

Whereas I will show that there is no convincing evidence to support the first three claims above, the last two claims appear to be plausible.

The next section presents the evidence for a "credit crunch" in aggregate data and the following section reviews the cross-sectional implications of the claims stated above, with the help of the individual bank balance sheet data from the CALL reports. The last section concludes by summarizing the claims' validity and the resulting implications.

1.2 Aggregate Data and its Implications for a "Credit Crunch"

Whereas, in general, the amount of outstanding debt of the non-financial sector has exhibited positive growth (Figure 1.1), the absolute amount of outstanding debt of non-financial businesses (Corporate and Non-Corporate) and households has declined sharply since Q4 2008, as the data from the Flow of Funds shows[2].

[2] The Flow of Funds data is obtained from the website of the Federal Reserve: www.federalreserve.gov.

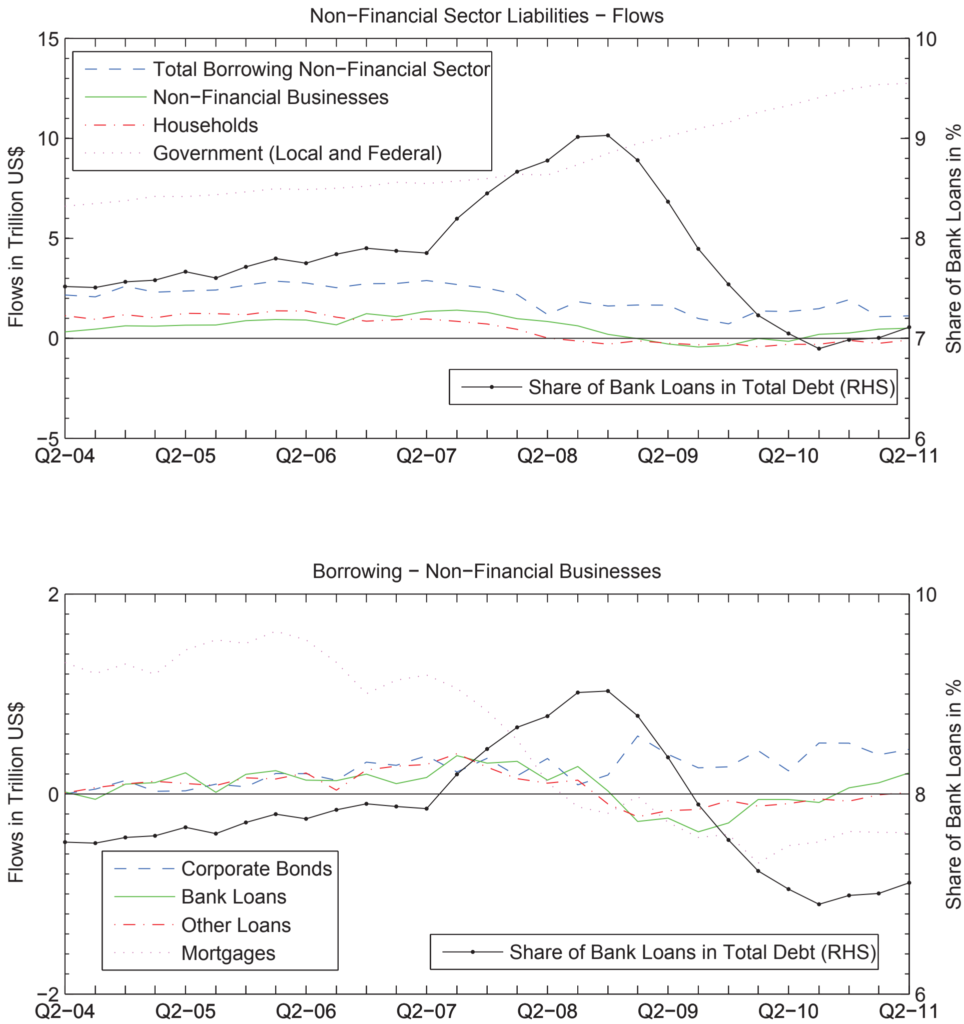
The government sector (federal and local) has provided for the overall increase in liabilities of the non-financial sector by borrowing on a large scale.

The reduction in lending to non-financial businesses *per se*, however, cannot be interpreted as evidence for a "credit-crunch". Firms have substituted bank lending for other forms of finance, which becomes evident from the constantly growing net bond issuances (Figures 1.1 and 1.2). While in the two years leading up to the crisis, the share of bank lending rebounded slightly, the degree of dependency on bank loans seems generally low, as bank loans account for less than one tenth of total liabilities. Still, this is not an indication of the irrelevance of bank loans for the economy in general. How vital bank loans are as a source of funding differs with firm size. Whereas small firms do not have immediate access to capital markets, since they normally cannot issue bonds or securitize their loans, large firms have clearly made use of other forms of finance, as the pronounced decline in the share of commercial bank loans in total credit market instruments of nonfinancial Corporations shows (Figure 1.2). The picture for Non-Corporate firms (Figure 1.3), on the other hand, looks quite different. Assuming that Non-Corporate firms are on average smaller than Corporations, smaller firms seem indeed more dependent on bank loans. The sharp decline in the share of bank lending after Q4 2008, which is accompanied by a negative change in liabilities, hints towards a more restrictive credit-supply in this respect. Notably, the decline in the share of bank loans cannot be due to increases in base capital[3], as net investment of proprietors is negative. Other loans (see the caption of Figure 1.1 for a definition) and trade payables are more resilient. However, for Non-Corporates those are only 40% and 25% of the size of outstanding bank loans, respectively. The by far largest part of non-corporate liabilities is constituted by mortgages, which are basically reducing to a net zero flow by 2009.

Hence, even though other forms of finance have not dried up as severely as bank loans, they also did not compensate for the shortfall.

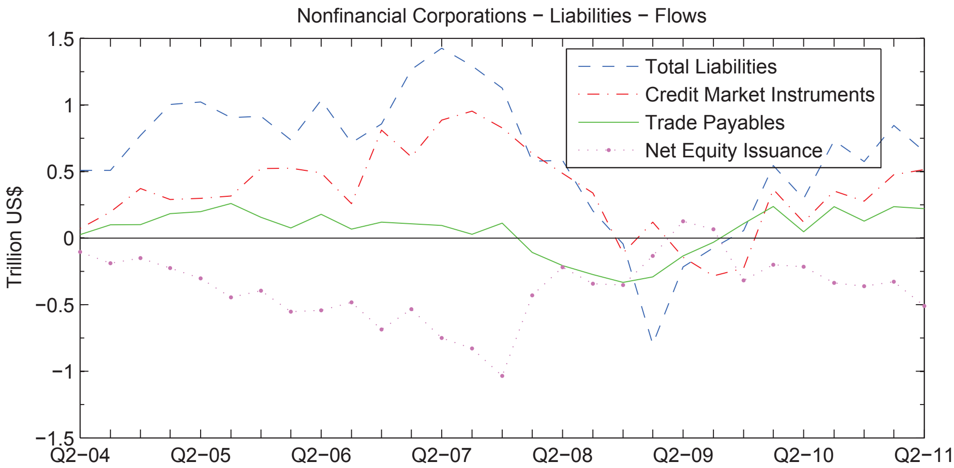
Still, the decline in bank loans is not a direct proof for a "credit crunch". After all, the demand for loans is likely to have plummeted because of the deteriorating macroeconomic environment. Nevertheless, a reduction in credit demand cannot explain why the *share* of bank loans in credit market instruments has declined. Obviously, bank loans were, on the margin, more difficult to obtain than other forms of financing.

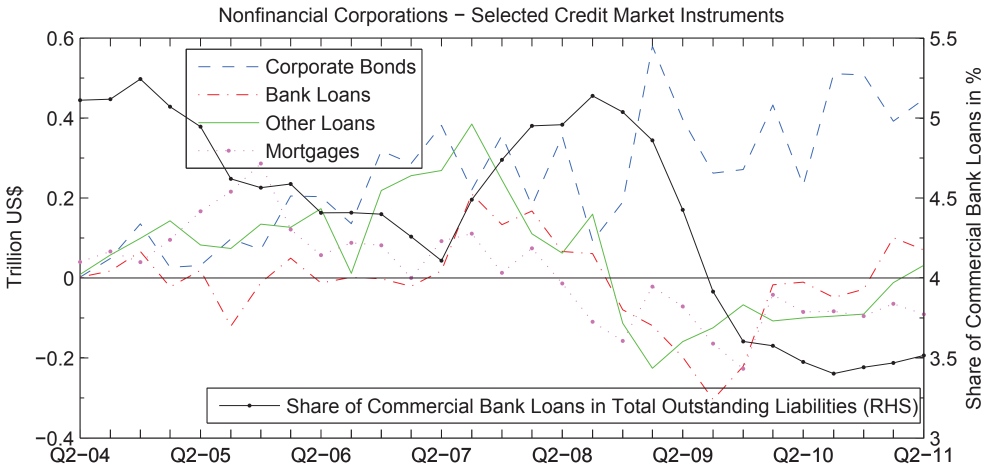
[3] As has been argued by Chari et al. (2008)



The upper graph shows the quarterly debt flows of selected non-financial sectors (left scale) together with the share of outstanding commercial bank loans in total debt of the non-financial sector (right scale). The lower graph depicts the liability flows of non-financial businesses, broken down into *Corporate Bonds*, *Bank Loans*, *Other Loans*, and *Mortgages*. *Bank Loans* are loans to non-financial sectors from US chartered banks and foreign bank offices in the US only. Loans from banks with foreign residency are included in *Other Loans*, as well as syndicated loans, loans from Credit Unions, Finance Institutions, Asset Backed Securities Issuers, the Government, and Government Sponsored Enterprises. Flow data is seasonally adjusted. Source: Flow of Funds (Tables F.2 and L.101) , Federal Reserve website www.federalreserve.gov

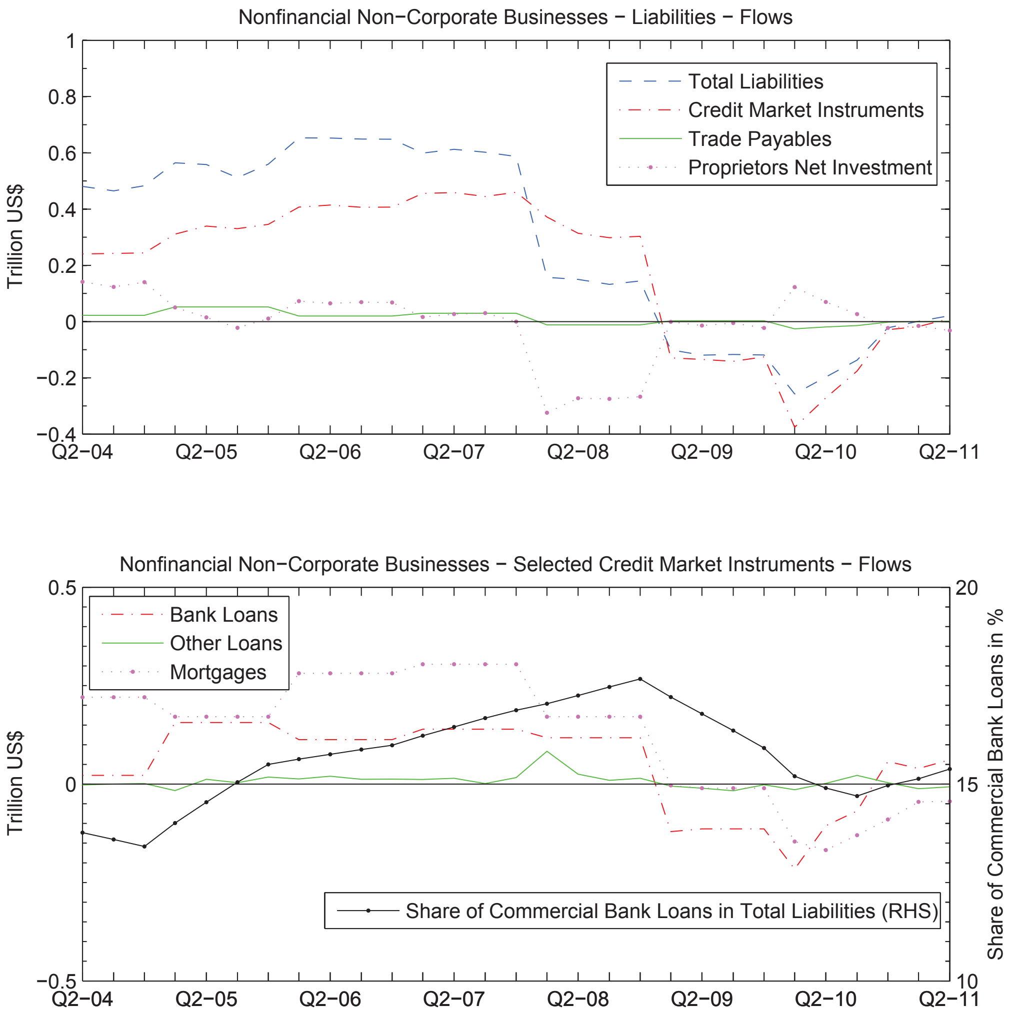
Figure 1.1: Outstanding Debt and Bank Loans - Non-Financial Sector





The upper graph depicts the quarterly flow of non-financial corporate liabilities, whereas the lower graph shows selected components of credit market instruments (left scale) as well as the share of commercial bank loans in total outstanding liabilities (right scale). *Bank Loans* are loans to the non-financial corporate sector from US chartered banks and foreign bank offices in the US only. Loans from banks with foreign residency are included in *Other Loans*, as well as syndicated loans, loans from Credit Unions, Finance Institutions, Asset Backed Securities Issuers, the Government, and Government Sponsored Enterprises. Flow data is seasonally adjusted. Source: Flow of Funds (Tables F.102 and L.102), Federal Reserve website www.federalreserve.gov

Figure 1.2: Total Borrowing and Bank Loans - Non-Financial Corporate Businesses

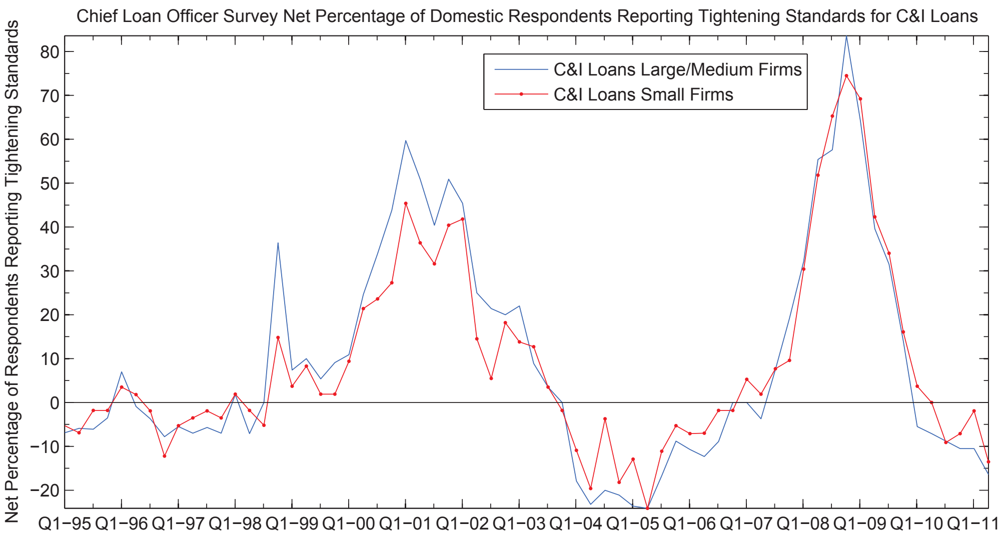


The upper graph depicts the quarterly flow of non-financial non-corporate liabilities, whereas the lower graph shows selected components of credit market instruments (left scale) as well as the share of commercial bank loans in total outstanding liabilities (right scale). *Bank Loans* are loans to non-financial non-corporate sector from US chartered banks and foreign bank offices in the US only. Loans from banks with foreign residency are included in *Other Loans*, as well as syndicated loans, loans from Credit Unions, Finance Institutions, Asset Backed Securities Issuers, the Government, and Government Sponsored Enterprises. Flow data is seasonally adjusted. Source: Flow of Funds (Tables F.103 and L.103), Federal Reserve website www.federalreserve.gov

Figure 1.3: Total Borrowing and Bank Loans - Non-Financial Non-Corporate Businesses

Some caveats are in order. Non-corporate businesses are not exclusively small businesses. In fact, the small and medium sized businesses, which were supposedly hit hardest by the insufficient supply of credit, are Corporations. Also, the data for non-corporate businesses in the Flow of Funds is merely an approximation. It is based on the annual Statistics of Income[4] and the quinquennial Survey of Small Business Finances conducted by the Federal Reserve. It is unclear, how good an approximation this is, and as such, may contain large errors. In this respect, the CALL report data can provide a much better estimate, as filing banks provide detailed information on small business loans.

Another important source of information for the advocates of a "credit-crunch" is the Chief Loan Officer survey data. In Figure 1.4, the net percentage of domestic respondents (firms) reporting tightening standards for commercial and industrial (C&I) loans is plotted over time, for both small and medium/large firms. A percentage of zero indicates that, on average, standards are neither tightening nor relaxing. Starting from Q3 2007, credit standards were tightening rapidly.



Net percentage of respondents (firms) of the Chief Loan Officer Survey, which reported tightening credit standards for C&I loans. The blue line represents respondents of small firms, whereas the red line pertains to respondents of medium-market and large firms (annual sales of $50 million or more). Source: Chief Loan Officer Survey, Federal Reserve website www.federalreserve.gov

Figure 1.4: Chief Loan Officer Survey - C&I loans

[4]The Statistics of Income Survey (SOI) is conducted by the IRS on an annual basis, utilizing the data on tax filings.

In Q4 2008, a net percentage of above 70% of all respondents reported tightening standards. This number is also significantly larger than what has been observed after the “dot-com bubble” in 2000 and 2001. Nevertheless, the information content with respect to restrictions in the supply of credit is limited. Firstly, it does not imply how restrictive the supply of credit was in absolute terms. Given that standards were most probably too soft in previous periods, tighter standards rather indicate a return to more sustainable lending practices. Secondly, tightening standards do not necessarily imply a lack of funding for economically viable firms. Thirdly, the number of respondents is quite small (usually less than 60 chief loan officers do reply), such that the survey data might not be representative or suffer from an endogenous selection bias, as institutions with apparent issues or problems may be more likely to reply.

Interestingly, there is not much of a difference in the response between smaller and large firms. If smaller firms were really hit harder by the credit crunch, then it is not reflected in the Chief Loan Officers Survey.

1.3 The Bank Perspective

To shed more light on the observed aggregate patterns, this chapter will take the perspective of the lenders. Alongside, the claims about the banking sector weaknesses from above are addressed. The analysis is based on the dataset published by the *Federal Deposit Insurance Corporation* (FDIC)[5], which consists of the quarterly US CALL report data. The sample under consideration runs from Q4 1992 until Q2 2011[6]. Given that it covers all the banks chartered in the US, as well as savings banks and savings associations, the sum of bank loans from all institutions in the sample is a sensible approximation to aggregate bank lending[7]. Savings banks and associations are fairly important providers of real estate loans and small C&I loans, as Figure 1.5 shows. Small loans are defined as loans with a face value of less than 250,000 US Dollar[8]. It is highly unlikely, that large firms

[5]The data is publicly available for download at http://www2.fdic.gov/sdi/

[6]To obtain more compact graphs, usually a shorter sample is used. Only if earlier periods exhibit different trends or are vital for the interpretation of the data, the full sample is employed.

[7]It is not exactly equal to the economy-wide aggregate, as the dataset neither covers branches and agencies of foreign banks in the US nor direct loans from banks residing in foreign countries. Branches and agencies of foreign banks, however, make up a large share of total commercial and industrial lending in the US (up to 21.2% in the last decade). Less detailed data is publicly available through the FFIEC 002 forms, but is in general insufficient or not applicable for the purposes of this paper. Hence, the analysis here restricts itself to US chartered banks and FDIC insured branches and agencies of foreign banks. Where the lack of information on foreign bank loans is crucial to the argumentation, I will provide approximations of the possible impact of foreign bank offices’ activities.

[8]This definition for small loans is common in the literature. See for example Ashcraft (2006).

would opt to demand such small loans[9]. Therefore, it seems reasonable to assume that, on average, small loans are also flowing to small firms. In this sense, savings institutions appear as a non-negligible provider of funding for small firms.

Table 1.1 presents an overview of the institutions in the sample. For reasons of simplicity, all institutions shall be referred to as banks. Further details of the FDIC dataset are presented in the Appendix.

Percentile Interval	*<25%*	*50%*	*66%*	*80%*	*90%*	*95%*	*99%*	*>99%*
Share in Agg Lending	0.847	2.2	2.6	3.8	5.2	5.4	17.4	62.5
Number of Savings Institutions	248	300	249	272	259	152	117	22.1
Number of Commercial Banks	2282	2230	1369	1144	751	353	286	79.7
- under Federal Charter	432	551	379	361	247	129	122	46.7
- under State Charter	1850	1679	989	782	504	225	163	33.0
Observations (per Quarter)	2532	2532	1620	1418	1013	506	405	102
Observations (Total - in Thousand)	179.7	179.7	115	100.6	71.9	36	28.8	7.2

The *Percentile Intervals* refer to the different size groups. The group of the smallest banks, denoted by a percentile interval of *<25%*, includes the 25% smallest institutions according to the value of total assets. All groups are exclusive. Thus, the second percentile interval, *50%*, contains the 50% smallest institutions, exclusive of the 25% smallest institutions of the previous size group. The group of the largest banks, *>99%*, is comprised of the 1% largest institutions. The presented statistics are based on the cross-section- and time-averages over the full sample, from Q4 1992 until Q2 2011. The respective numbers of institutions are quarterly averages. *Observations (Total)* denotes the total number of observations in the respective size group over all quarters.

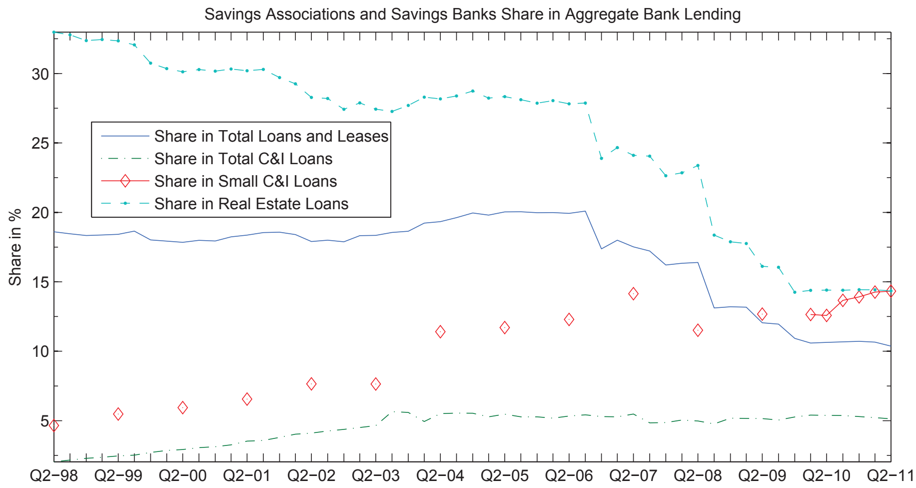
Table 1.1: Summary Statistics

1.3.1 Bank Size and Small Business Loans

Small banks do dominantly provide small loans, as Figure 1.6 confirms. This is particularly true for C&I loans. As small banks most likely have smaller firms as costumers, this figure confirms that small loans are mainly flowing to small firms. However, it is not true that small banks are the main providers of small business loans. The largest 1% of banks and savings institutions are actually providing the bulk of small C&I loans (Table 1.2).

The central observation, however, is that the evidence for a "credit crunch" in small business loans is mixed at best. Apart from a relatively small 5% decline from 2008 to 2009, which compares to a decline in nominal GDP of around 2.6% in the same period, there is no sign for an extreme reduction like in the aggregate

[9]Note that C&I loans include neither commercial real estate loans nor trade credit.

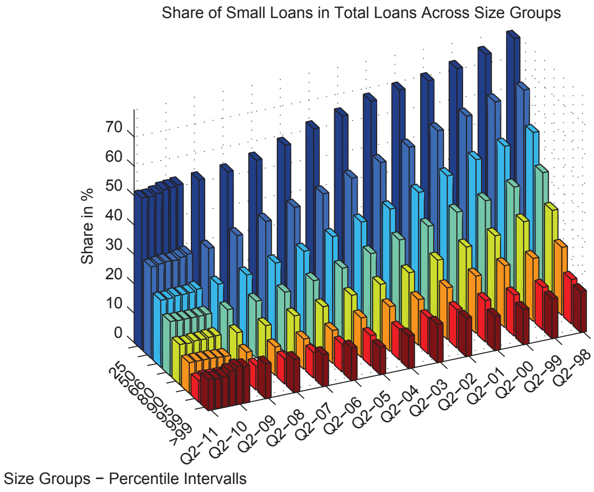


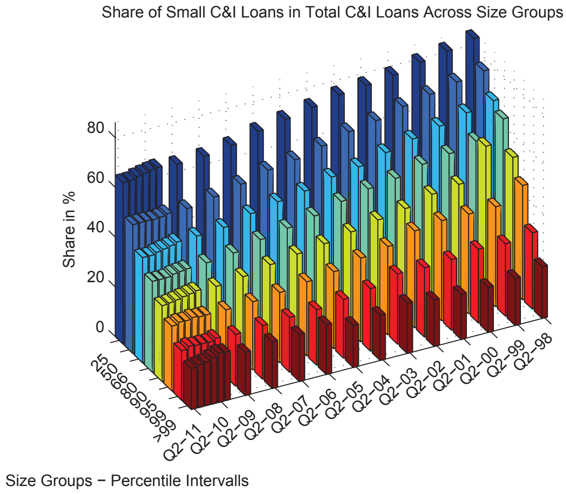
The shares are calculated as the sum of outstanding loans by savings institutions (savings banks and savings associations) relative to the sum of outstanding loans of all deposit taking institutions. Small C&I loans, are commercial and industrial loans (no commercial real-estate loans or trade credit) with a face value of less than 250,000 US$. *Real Estate Loans* comprise both, commercial and private real estate. Tables 1.4 and 1.5 in the Appendix provide more detailed definitions.

Figure 1.5: Share of Savings Institutions in Aggregate Lending

series. The largest banks even exhibit an increase in the outstanding small business loans from Q2 2009 to Q2 2010. Overall, the reduction in small C&I loans is far less severe than the reduction in total C&I loans, at least until Q2 2010 (Figure 1.7).

As explained in footnote 7, non-insured branches and agencies are not covered in the sample, which may greatly distort the findings. These institutions are generally regulated by the Federal Reserve Banks and do not have to file quarterly CALL reports. But, they are required to file a so called FFIEC 002 form, which contains a subset of the CALL report items. Unfortunately, the information on Small Business Loans is only required for insured institutions, which are members of the FDIC dataset already.





The upper graph shows the average ratio of small loans to total loans for the respective size groups. The share for an individual bank is calculated as the sum of outstanding small loans (face value of 250,000 US$ or less, for all loan types for which the data is available), divided by the sum of the total values of the corresponding loan types. The depicted average share is the average among all institutions within the respective size group for a given quarter. The loan types for which the amounts of small loans are available are: loans secured by nonfarm nonresidential properties, C&I loans to US addresses, loans secured by farmland, and loans to finance agricultural production. Small loans are reported in annual frequency in Q2 of every year and from Q1 2010 onwards in quarterly frequency. The lower figure presents the ratio of outstanding small C&I loans divided by total amount of outstanding C&I loans. For definitions see Tables 1.4 and 1.5 in the Appendix.

Figure 1.6: Share of Small Loans in Total Loans for Different Bank Sizes

	Small C&I loans (billion US$)				
Percentile Interval	*2007*	*2008*	*2009*	*2010*	*2011*
25	4.0	4.2	4.2	4.0	3.7
50	9.8	9.6	8.7	8.1	7.3
66	9.4	9.2	8.4	7.7	7.0
80	11.5	11.4	10.7	9.2	8.4
90	13.9	13.5	13.3	11.4	10.2
95	11.4	11.7	10.6	9.7	9.4
99	29.9	30.4	28.2	20.2	18.2
>99	98.8	109	105	118	103
Total	189	199	189	188	167

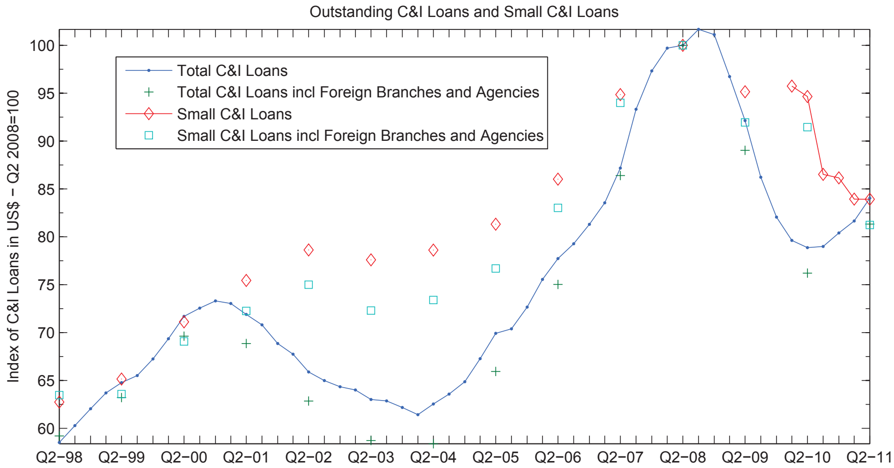
The numbers are calculated as the cross-sectional sum over all institutions within the respective size group (see Table 1.1). Small loans (face value of 250,000 US$ or less) are reported in annual frequency in Q2 until 2009, and in quarterly frequency from Q1 2010 onwards. The numbers displayed are for Q2 of each respective year.

Table 1.2: Absolute Value of Small C&I Loans

Hence, the data from the FDIC CALL reports is a relatively precise measure of small business loans, given the lack of availability of more comprehensive measures. Nevertheless, as a rough approximation of how foreign bank branches and agencies may influence the dynamics of the series, Figure 1.7 shows the aggregate C&I loan numbers obtained from the FDIC dataset together with a series that includes foreign bank branches and agencies, based on the annual report of the Federal Reserve Board *Structure and Share Data for U.S. Banking Offices of Foreign Banking Organizations.* As the report only provides data for aggregate C&I loans, I am using the share of small C&I in total C&I loans obtained from the CALL reports as a benchmark, to approximate the value of small C&I loans of foreign bank branches and agencies. Even though the reduction in loans is more pronounced, small C&I loans are still faring significantly better than the total C&I loans based on the CALL report data in 2008/2009.

The limited decrease in the aggregate value of small business loans could alternatively be explained by a general decrease in the face value of newly issued loans, such that more loans would be classified as "small". While this possibility cannot be precluded, the group of banks, which belong to the 5 to 1% largest institutions (95% to 99% percentile interval of the size distribution) shows, however, a sizable decline in the value of outstanding small business loans[10]. Additionally, the other size groups do not exhibit an absolute increase, whilst the reduction in their total

[10]Note that this is not due to the merger of Wachovia and Wells Fargo, as both banks belong to the group of the 1% largest banks in the entire sample.



Data on C&I loans of *Foreign Banks' Branches and Agencies* is taken from the Federal Reserve Board's report on *Structure and Share Data for U.S. Banking Offices of Foreign Banking Organizations*. Small C&I loans of Foreign Branches and Agencies are approximated by using the share of small business loans to total C&I loans from the FDIC dataset multiplied with total C&I loans of foreign branches and agencies. C&I loans of Foreign Branches and Agencies are end of the year (Q4) data, but are treated as Q2 data to coincide with the CALL report filing dates on small business loans (Q2 from 1998 - 2011).

Figure 1.7: The Dynamics of Small C&I Loans

C&I lending is relatively modest. If a significant trend towards smaller loan sizes had indeed taken place, then one would expect to see an increase in both the share of small loans and the absolute value.

A more serious shortcoming of the data is the aggregate nature of C&I loans, even on a bank-individual basis. Firstly, it is unclear whether the relative stability of outstanding loans can be ascribed to a renewal or extension of existing loans, or to the supply of new loans[11]. Secondly, the dataset does not allow to distinguish between commercial and industrial loans. It could still be the case, that loans to manufacturing/industrial businesses have been cut down significantly, whilst other commercial businesses were able to secure additional funding.

Notwithstanding the shortcoming of the dataset as to the lack of information about the receivers of the loans, there is no visible evidence for an overly pronounced decline of loans to small businesses from the CALL report data. Even if

[11] The dataset does provide information on the number of outstanding loans, which is declining more strongly than the outstanding amount. Still, this information is again ambiguous, as businesses could have started to demand loans of relatively larger size, or, the number of very small loans to very small businesses could have been reduced, in favor of slightly larger firms. The CALL report data does not allow to determine the maturities of small business loans, either.

smaller banks had indeed been hit harder by the recent financial crisis, because they did not receive direct government support like some of the largest banks, the overall impact would have been relatively small, as the main part of small business loans comes from the 1% largest banks. Those have indeed alleviated the reductions in small C&I lending and helped to partly insulate credit supply to small businesses. Only recently, since 2010, a more pronounced decline in small business loans is visible. Given that this deterioration happened 2 years after the height of the crisis, a direct impact from the financial turmoil is unlikely. A negative impact of very low economic growth and rising default rates among small and medium sized businesses is a more plausible explanation in this respect. Overall, the 5% decline in small business C&I loans from Q2 2008 until Q2 2010 is rather small, given the weak economic outlook at that time. In addition, as Figures 1.2 and 1.3 suggest, other forms of finance have held up relatively well. Overall, the evidence for overly restrictive financing conditions of small businesses is very limited.

1.3.2 Bank Capital

The lack of bank capital has been portrayed as the most severe problem of the banking sector during the crisis. Figure 1.8 depicts the development of bank capital ratios over time for several size groups. In general, larger banks work with a higher leverage than smaller banks, but are still well capitalized. The minimum core equity capital ratio according to the new Basel III proposals, including the maximum amount of anti-cyclical capital buffers, is not more than 7%, which is well below the observed averages. Core equity ratios were even increasing slightly until Q3 2007. With the rise of default rates of mortgage backed securities starting at the end of 2007, core equity ratios clearly declined across all size groups. Thereafter, only the largest banks managed to increase their base capital ratios, both by receiving direct capital injections from the government and by issuing new equity in the market.

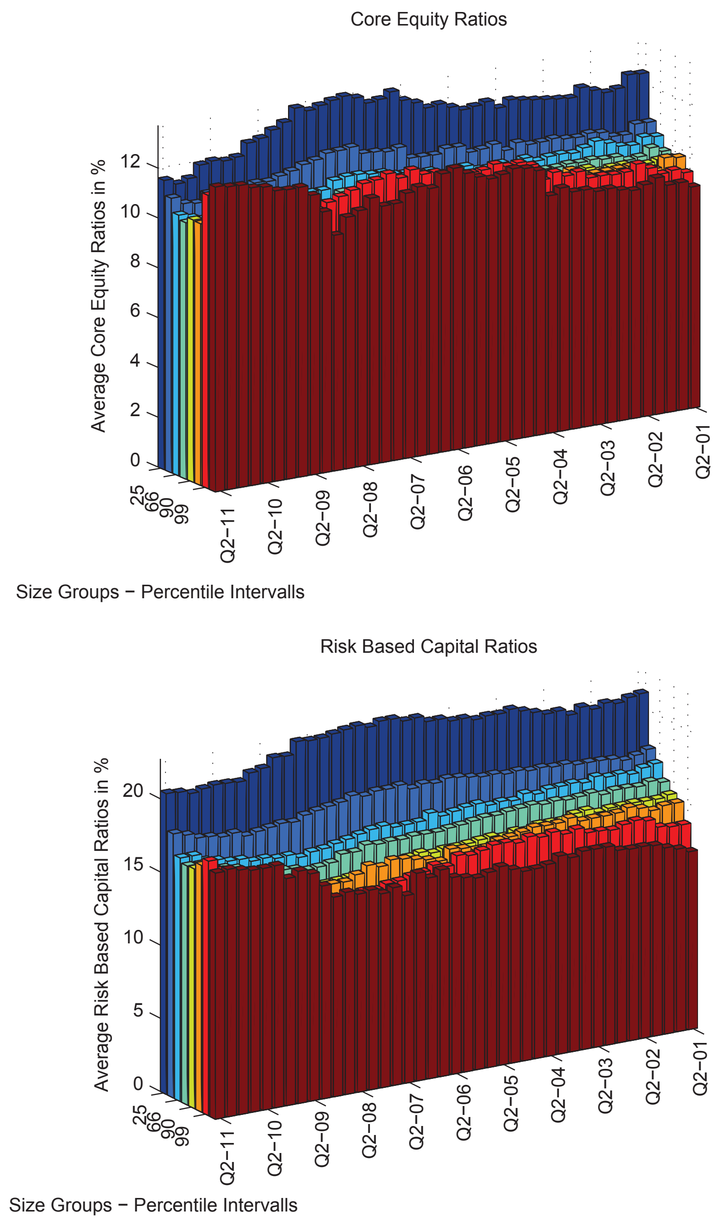
The picture for risk based capital (risk weighted Tier 1 + Tier 2 capital) looks similar. The average capital ratios are way beyond the regulatory minimum of 8% and the newly proposed Basel III risk based capital requirement, which does not exceed 10.5%. It is striking, however, that although core equity ratios are rising slightly for most size groups until Q3 2007, this is not the case for the risk based capital ratios. This suggests that risk taking picked up and therefore the risk weights for bank assets increased, leading to a lower risk-weighted capital ratio. Notably, this is does not reflect the very optimistic ratings and calculated risks that prevailed before Q3 2008. With more conservative risk estimates, the decrease in risk based capital ratios would have looked much more severe. Moreover, the wave of securitization from 2005-2008 led to outsourcing of relatively risky assets, which is not reflected at all on banks' balance sheets[12]. If anything, a proper declaration of off-balance sheet assets on banks' balance sheets would have led to a further reduction in the risk-based capital cushions. Whether it would have also led to a reduction in core equity ratios is not fully clear, but it appears exaggerated to assume that average capital ratios would be reduced to a level close to the regulatory minimum.

Nonetheless, the aggregated average capital ratios are not necessarily the measure of interest in this respect. A small number of under-capitalized banks may already be enough to cause serious problems in the banking sector. In this sense, the tails of the capital ratio distribution are of greater interest than the simple averages. Hence, to address any questions and arguments about under-capitalization, a look into disaggregated data is pivotal.

And indeed, despite the relatively comfortable capital cushions of most banks, a significant number of deposit taking institutions experienced serious problems. Figure 1.9 plots the share of institutions in the respective size group, which are capital constrained. A capital constrained bank is defined as an institution with a core capital ratio of less than 6% and a total risk-based capital ratio of less than 10%. Whereas the difficult times in terms of capital for the 1% largest banks started in Q3 2007, when problems with mortgage backed securities became apparent and the first Hedge-Funds had to close, the difficult periods for smaller institutions began with the collapse of Lehman Brothers in Q3 2008. Note that around 15% (which is an absolute number of 9-10) of the largest banks had core equity ratios below 6% at the end of 2007. The lower panel of Figure 1.9 depicts the total shortfall of core equity relative to a 6% minimum ratio. The 2008 financial crisis clearly stands out, which is only partly explained by the growth of the financial sector in general.

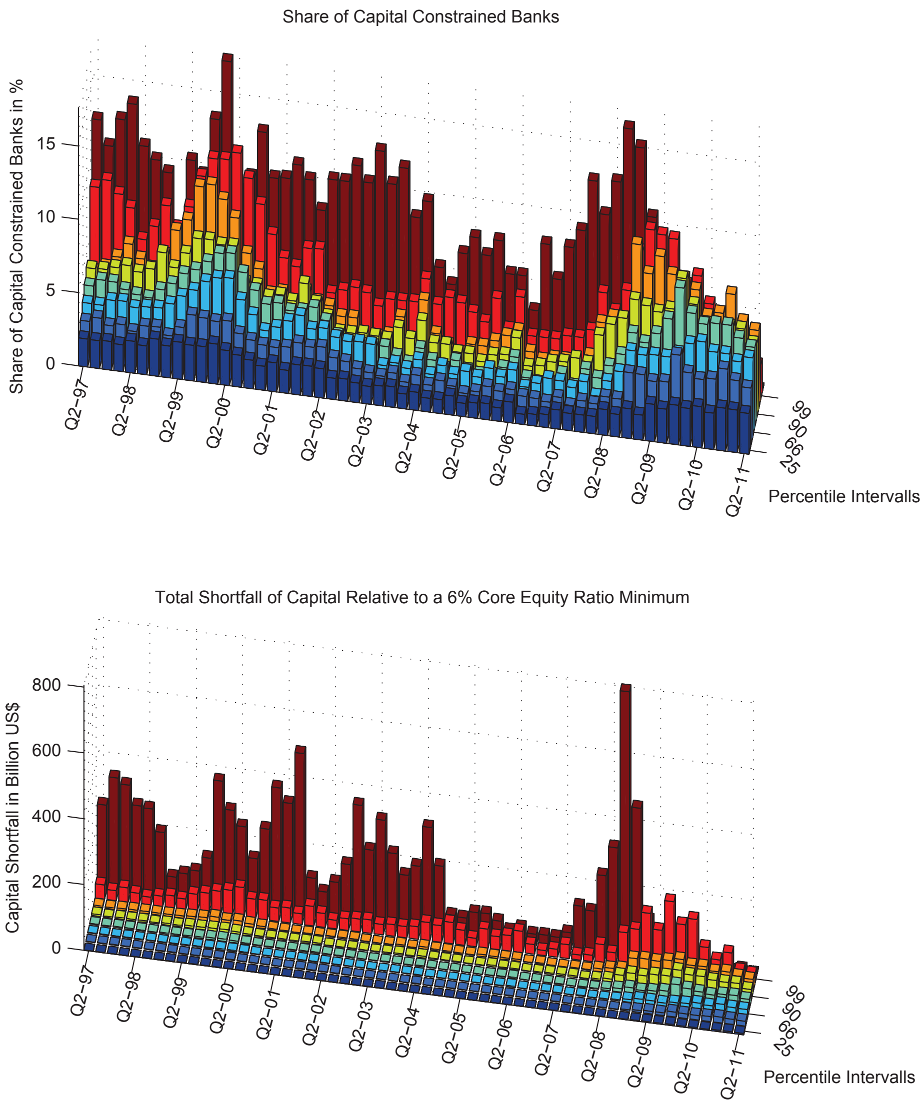
Depending on the minimum core equity ratio used, the total shortfall in capital can be enormous. Table 1.3 highlights, that in order to reach the future minimum core equity ratio of 7% envisaged by Basel III, a *ceteris paribus* raise in equity of currently $337bn would be required; most of it demanded by the medium sized and larger institutions. The 1% largest institutions have, due to both government support and equity issuances, been able to raise a significant amount of capital already, which puts them in a stronger position.

[12]See Brunnermeier (2009)



The upper panel shows the average ratio of core equity over total assets, whereas the lower panel depicts the average ratio of Tier 1 + Tier 2 capital over total risk adjusted assets. The averages are calculated as the arithmetic average over all institutions within the respective size groups in a given quarter. The size groups are classified as described in Table 1.1. For definitions see Tables 1.4 and 1.5 in the Appendix.

Figure 1.8: Bank Capital Ratios



The upper panel shows the share of capital constrained banks within the respective size group. Banks are defined as capital constrained if their core equity ratio is less than 6% and/or their total risk-based capital ratio (ratio of Tier 1 + Tier 2 capital over total risk adjusted assets) is less than 10%. The lower panel shows the sum of the shortfall of core equity of all capital constrained banks towards a 6% minimum requirement, within the respective size groups. The size groups are classified as described in Table 1.1. For definitions see Tables 1.4 and 1.5 in the Appendix.

Figure 1.9: Capital Constrained Banks

	Min Core Equity Ratio			
	4.5%	*5%*	*6%*	*7%*
Q4 2007	6.4	8.5	154	791
Q4 2008	168	270	692	2179
Q4 2009	143	200	390	795
Q4 2010	111	151	257	485
Q2 2011	66.9	92.8	162	337

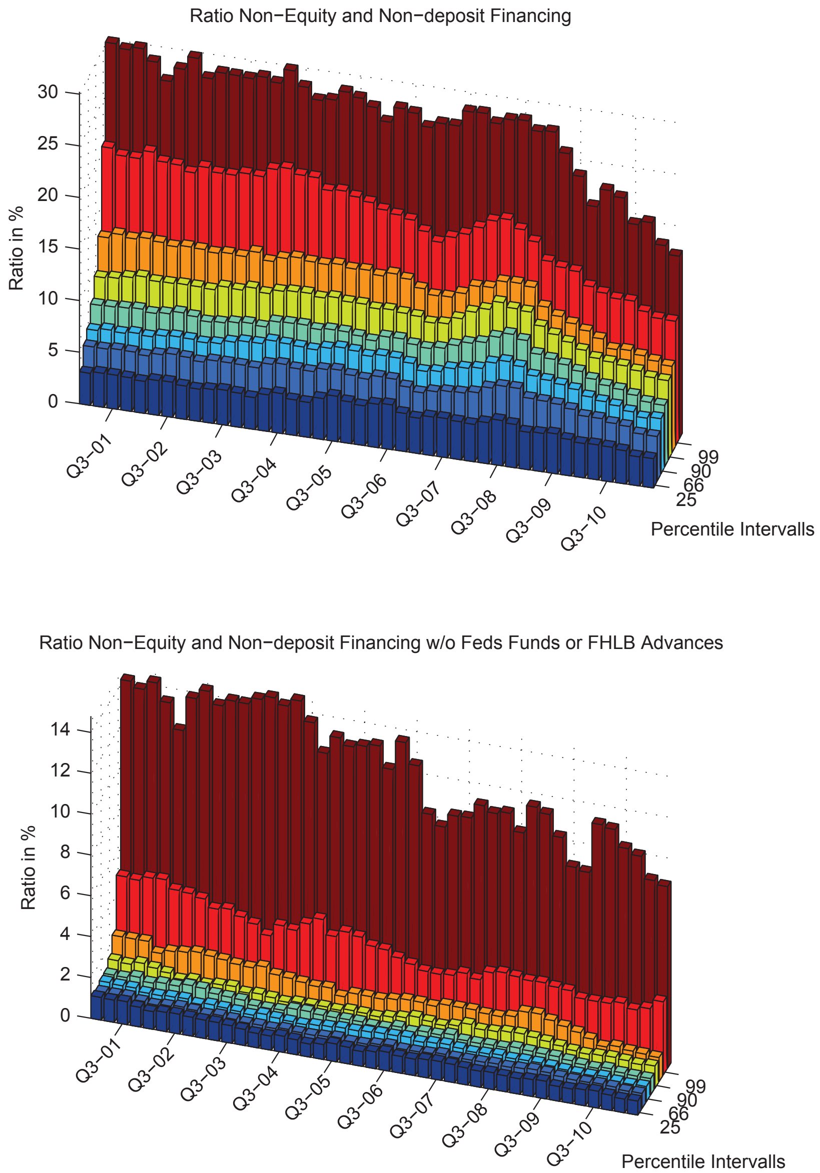
Capital shortfall in billion US dollar. The shortfall is calculated as the cross-sectional sum of the shortfall of core equity of all capital constrained banks, relative to the respective *Minimum Core Equity Ratio* given.

Table 1.3: Capital Shortfall in Billion US Dollar

Overall, the cross-section of bank capital suggests that the majority of institutions had sufficient capital cushions. However, some individual institutions, which obviously took on too much risk, suffered from a severe lack of capital during the recent crisis and are still far short of fulfilling future regulatory minimum requirements. The largest institutions, which experienced the largest capital shortfalls, managed to shore up their capital ratios after Q3 2008, whereas more than 5% of all other banks are still short of equity, given their total assets.

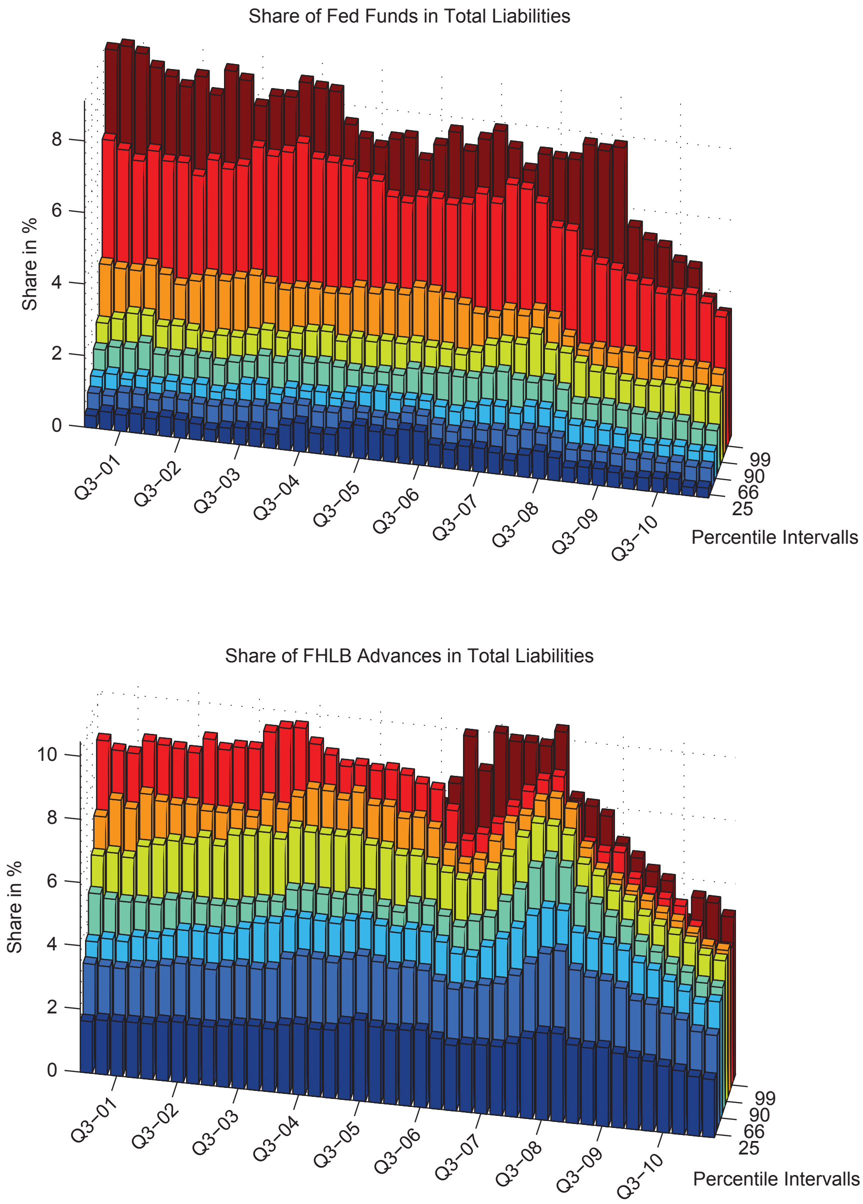
1.3.3 Sources of Funding

Surprisingly, with the development of new debt instruments, the degree of non-equity and non-deposit financing (external financing) has not increased, as Figure 1.10 illustrates. Larger banks have also a higher degree of external finance, but there is clearly no visible upward trend, even for the 1% largest institutions. Especially, when external financing excluding Fed Funds and Federal Home Loan Bank (FHLB) advances is considered, the general trend is pointing downwards. Prior to the recent crisis, from Q1 2006 until Q3 2007, external financing ratios among the larger 50% of institutions were indeed increasing, but the increases amount to less than 5% of total liabilities on average. Overall, the external financing ratios are relatively low. Even the largest banks still rely to more than 70% on equity and deposits for funding. Figure 1.11 visualizes the share of Fed Funds and FHLB advances in total liabilities. In particular, the FHLB advances make up a larger share of total liabilities during the crisis. Noteworthy is also the importance of the Federal Home Loan Bank advances relative to Fed Funds (Figure 1.11).



The upper panel shows the average ratios of non-equity and non-deposit liabilities over total liabilities (external financing ratio) within the respective size groups. The lower panel presents the average ratios of non-equity and non-deposit liabilities without Fed Funds and FHLB advances over total liabilities. The averages are calculated as the arithmetic average over all institutions within the respective size groups in a given quarter. The size groups are classified as described in Table 1.1. For definitions see Tables 1.4 and 1.5 in the Appendix.

Figure 1.10: External Financing Ratio



The upper panel shows the average ratios of Fed Funds liabilities over total liabilities, whereas the lower panel presents the average ratios of FHLB advances over total liabilities. The averages are calculated as the arithmetic average over all institutions within the respective size groups in a given quarter. The size groups are classified as described in Table 1.1. For definitions see Tables 1.4 and 1.5 in the Appendix.

Figure 1.11: Fed Funds and FHLB Advances as a Share of Total Liabilities

The FHLB system is on average responsible for more funding than the Federal Reserve; for institutions of all sizes[13]. It is also striking that, again, large institutions rely to a greater extent on the aforementioned types of external financing, even though they are, in principle, accessible to all banks.

Hence, the general picture which emerges does not hint at an extreme increase in the reliance on capital market funding, but does emphasize the *de facto* lender of last resort functions of both the Federal Reserve and the Federal Home Loan Bank system.

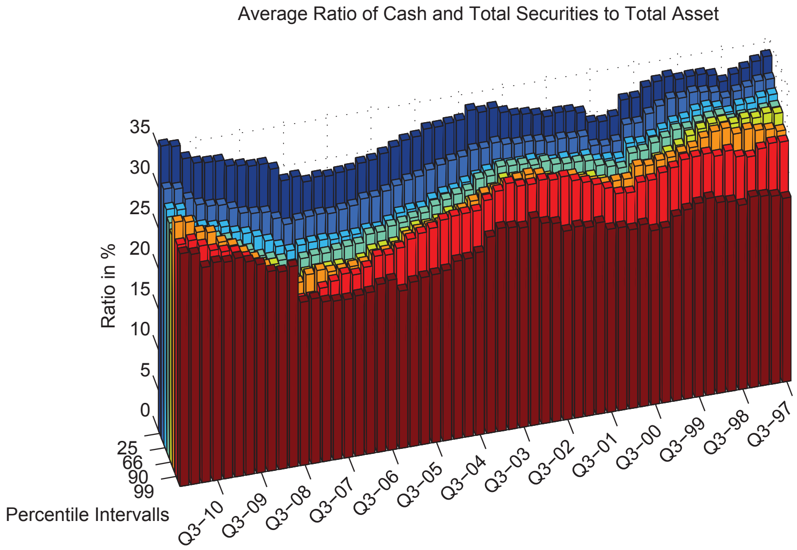
1.3.4 Liquidity

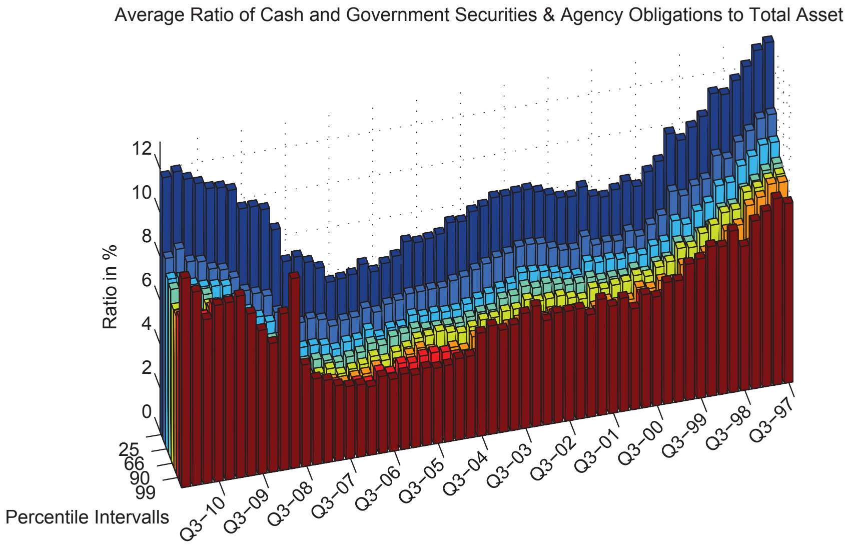
Banks' liquidity ratios, as plotted in Figure 1.12, show a significant downward trend until Q3 2008. Large banks have significantly less liquid balance sheets compared to smaller institutions; especially when only government agency obligations are counted towards liquid securities. In addition, they exhibit the largest declines in liquidity ratios from 2003 until Q3 2008.

Whether the observed liquidity ratios are sufficient or too low depends on several factors, most importantly the maturity of liabilities, which unfortunately cannot be assessed with the underlying dataset. Nevertheless, the fact that after Q3 2008 the amount of liquid assets jumped up and remained on a high level, suggests that banks' liquid asset ratios were insufficiently low. In addition, the decline in the liquidity ratios suggest that in exchange for assets which can serve as liquidity buffers, less liquid assets were purchased, which generally increases the risk of default. In conjunction with the increased use of short-term liabilities like commercial paper (see Brunnermeier (2009)), large banks appear quite vulnerable to liquidity shocks. For the small institutions this seems less of a problem, as their liquidity ratios are higher on average and they rely mainly on relatively stable sources of funding like deposits, Fed Funds and FHLB advances (see previous section).

The picture is more illustrative, when the percentage of institutions with critically low levels of liquidity is beheld (Figure 1.13). In Q3 2007, a quarter of the 1% largest institutions exhibited liquidity ratios of less than 5%, and over 16% had liquidity ratios of less than 2%. In other words, if just 2% of the total liabilities cannot be rolled over, then those institutions are technically insolvent.

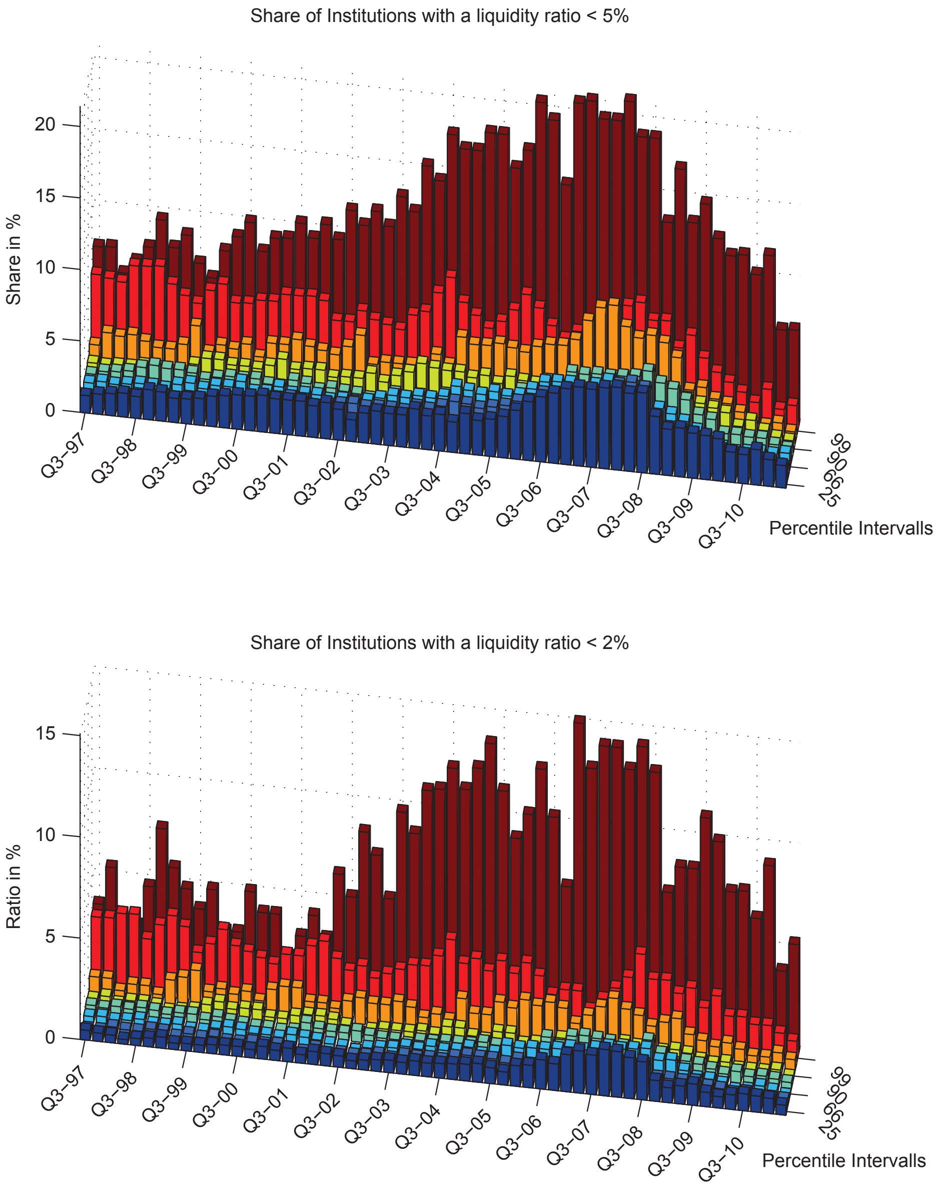
[13] See Ashcraft et al. (2010) for a more formal analysis regarding the FHLB as a lender for commercial banks and its role during the recent crisis.





The upper panel shows the average ratio of cash balances + total securities over total assets. The lower panel depicts the corresponding ratios, taking into account only government securities and government backed agency obligations instead of total securities. The averages are calculated as the arithmetic average over all institutions within the respective size groups in a given quarter. The size groups are classified as described in Table 1.1. For definitions see Tables 1.4 and 1.5 in the Appendix.

Figure 1.12: Liquidity Ratios



The upper panel depicts the share of institutions in the respective size groups, which exhibit a ratio of cash and government obligations over total assets (liquidity ratio) of less than 5%, whereas the lower panel shows the equivalent share for institutions with a liquidity ratio of less than 2%. The size groups are classified as described in Table 1.1. For definitions see Tables 1.4 and 1.5 in the Appendix.

Figure 1.13: Share of Institutions with Critically Low Liquidity Ratios

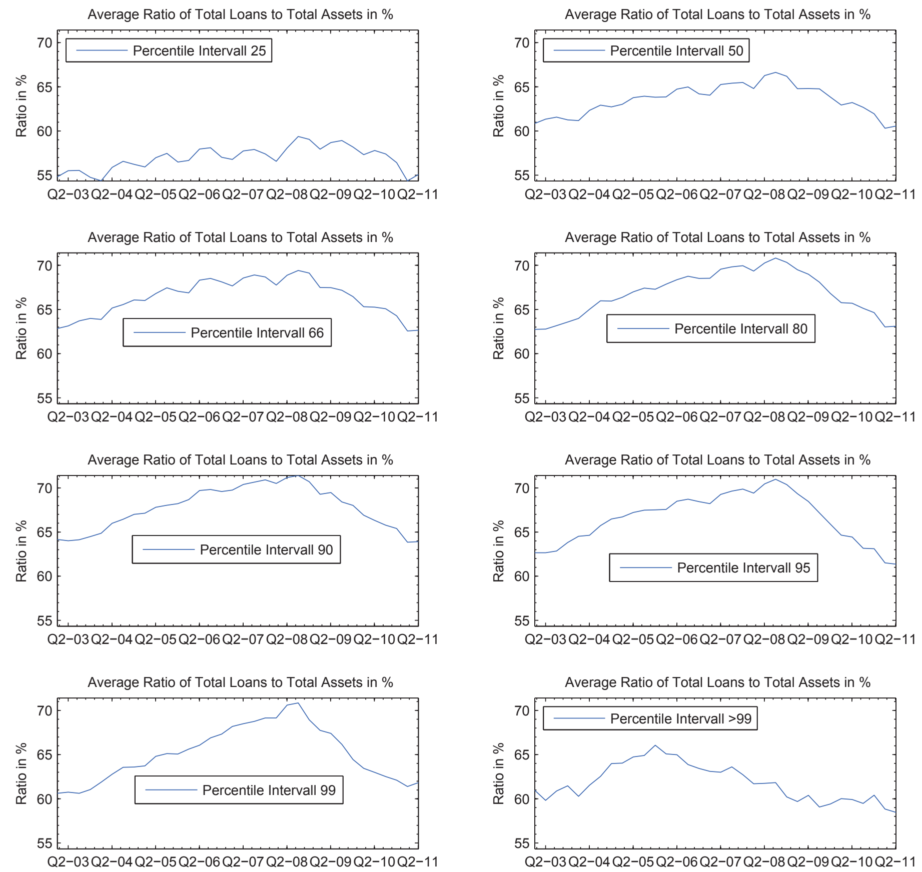
Overall, quite a few banks display very low liquidity ratios, especially between Q3 2007 and Q3 2008. The share of very large institutions with critical levels of liquid assets is unprecedented in the sample, and it distinguishes the recent crisis from the burst of the tech-bubble in 1999/2000. One possible explanation for the extremely tight liquidity management by large banks is the availability of *short-term* funding from the capital markets. If liquidity is readily available, then holding very liquid and low yielding assets is not efficient. On the other hand, this greatly increases the risk of default and corroborates the view that banks' business models grew riskier and more vulnerable to adverse shocks in the financial markets.

Since the data naturally covers only positions actually reported on the balance sheet, the ultimate liquidity position, however, may look significantly different. As both smaller and larger banks have removed significant amounts of principally illiquid mortgages from their balance sheets, either through securitization or sales to government sponsored enterprises like Fannie May and Freddy Mac, the liquidity risks were transferred to off-balance sheet vehicles and to government affiliated institutions. For larger banks, which provided liquidity backstop guarantees to their special purpose vehicles to which the relatively illiquid assets were laid off, liquidity was even more scarce than it is already implied by the CALL report data. This reinforces the general observation of very low liquidity ratios, especially among larger banks.

1.3.5 Risk Taking

As risk taking is not directly observable, precise statements are difficult to make. Nevertheless, several indicators and proxies can give a comprehensive view of how much risks banks took onto their balance sheets over time. One such proxy is the ratio of loans to total assets (Figure 1.14). Loans carry a relatively high risk of default compared to other assets, and they are not easily marketable and thus not liquid. With the exception of the groups of the smallest and largest banks, the share of loans in total assets clearly went up. The 1% to 5% largest banks increased the share of loans by 10 percentage points from Q1 2003 until Q3 2008. Notwithstanding the growth in total assets, the portfolio shift alone translates into an increase in lending of more than 15%.

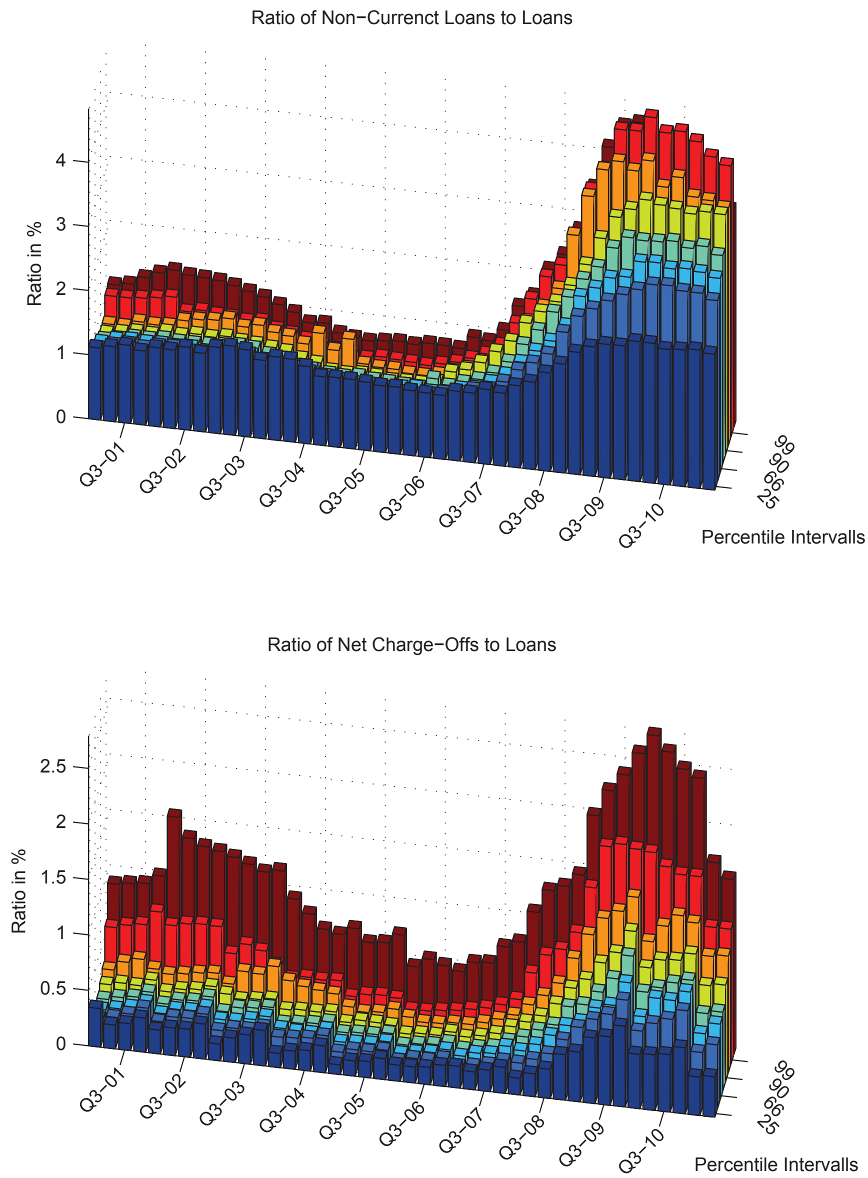
From this perspective, banks' business models seem to have become notably riskier, and the implied extra amount of supplied credit is substantial. Theoretically, the additional loans which were granted could have carried a lower or equal probability of default, compared to the existing loan portfolio. As Figure 1.15 suggests, *ex-post* this was not the case. Exactly those groups of banks, which more aggressively increased their loan shares, have also suffered from higher default rates on their credit portfolios. Given that the 1% largest banks have the highest ratio of charge-offs to loans over the whole sample, they obviously accumulated the loan portfolio with the highest risk of default. In general, the smaller banks seem to be much more conservative in their lending decisions. Figure 1.16 corroborates this view. Assuming that there is a trade-off between risk and return[14], the enormously high returns on equity, which the larger banks were able to generate until Q3 2007, are a hint towards the excessively high risks they took, relatively to the amount of core equity on their balance sheets.



The graphs show the average ratio of total outstanding loans over total assets for the respective size group. The averages are calculated as the arithmetic average over all institutions within the respective size groups in a given quarter. The size groups are classified as described in Table 1.1. For definitions see Tables 1.4 and 1.5 in the Appendix.

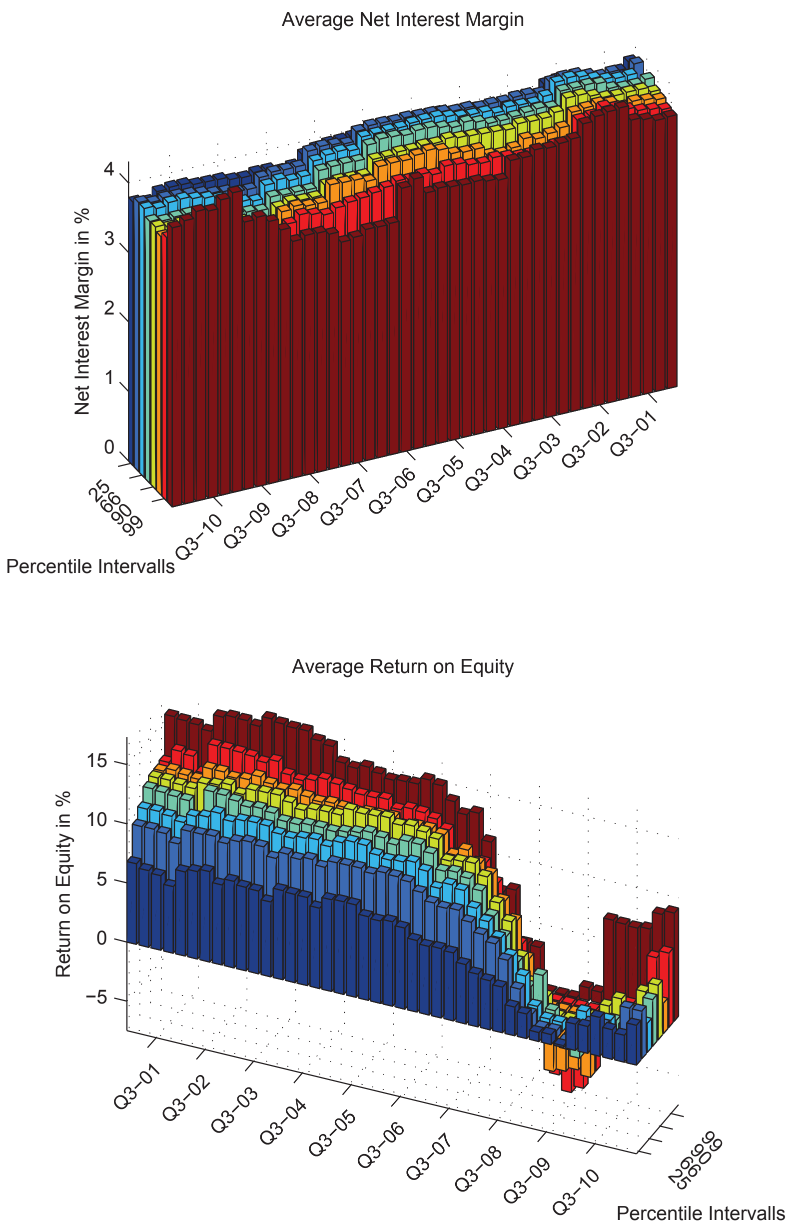
Figure 1.14: Ratio of Loans to Total Assets

[14]See Haldane et al. (2010) for evidence for a substantial trade-off between risk and return for financial institutions before and during the crisis.



The upper panel shows the average ratios of the total face value of non-current loans over total loans outstanding. The lower panel depicts the ratio of total effective charge-offs on loans over total loans outstanding. The averages are calculated as the arithmetic average over all institutions within the respective size groups in a given quarter. The size groups are classified as described in Table 1.1. For definitions see Tables 1.4 and 1.5 in the Appendix.

Figure 1.15: Non-Current Loans and Charge-Offs



The upper panel shows the average net interest margins, whereas the lower panel depicts the average return on equity. The averages are calculated as the arithmetic average over all institutions within the respective size groups in a given quarter. The size groups are classified as described in Table 1.1. For definitions see Tables 1.4 and 1.5 in the Appendix.

Figure 1.16: Net Interest Margins and Returns on Equity

Were these defaults expected? If banks expect a higher probability of default on a loan, they normally demand a higher rate of interest as a compensation. Figure 1.16, in contrast, shows that the net-interest margin banks charge does not vary much over time or across size groups. It seems that the default risk, which materialized with the crisis, was either not expected, or just not priced.

The average losses after Q3 2008 are very substantial for the larger banks and are more than likely to have an influence on their lending behavior. The smaller banks, on the other hand, did not suffer noteworthy losses on average.

1.4 Conclusion

Despite the tentative evidence of a decline in bank loans to Non-Corporates based on the aggregate data, and tightening credit standards from the *Chief Loan Officer Survey*, there is no evidence for a significant decline in small C&I loans. Assuming that small loans also flow to small businesses, the first claim that small firms experienced a sizable "credit-crunch" cannot be upheld. In addition, the bulk of small loans is issued by the largest 1% of banks, which disproves the central role of small banks for the provision of small business loans. Also, small banks were not hit harder by the crisis than larger institutions. Rather the contrary seems to be the case, as the descriptive evidence regarding capital ratios and risk taking suggests that small banks, on average, were more conservative and hence had relatively minor problems with delinquent loans.

The second claim, that banks in general exhibited insufficient capital ratios, cannot be confirmed either. Large banks did have lower capital ratios than small banks, but on average, capital ratios before and during the crisis seemed sufficient. However, some individual institutions suffered from a serious shortage of capital during the recent crisis. In total, around 5% of all institutions still seem under-capitalized, which is less severe than in the period after the burst of the "tech bubble" in 1999/2000. Still, the implicit demand of additional capital or requirements to deleverage in light of the new Basel III regulations are enormous.

An increased reliance on capital market funding cannot be detected in the CALL report data. Even the 1% largest institutions on average rely to more than 70% on equity and deposits as sources of funding. Striking is the importance of FHLB advances, which are responsible for a greater share in total liabilities than Fed Funds. This is clearly distorted by the fact that banks have moved significant amounts of assets off-balance sheet. Nevertheless, the largest part of banks' liabilities is constituted by equity and deposits, even after the collapse of many special purpose vehicles.

The last two claims, on the other hand, seem more plausible. Indeed, the amount of liquid assets on banks balance sheets was relatively low and a significant downward trend up until Q3 2007 can be observed. Particularly, the largest banks had such low liquidity ratios, that the inability to roll over even a small part of their liabilities, would have most likely meant insolvency in the absence of the extraordinary liquidity provisions by the Federal Reserve.

Finally, there is ample evidence for increased risk taking up until Q3 2007. Again, the largest institutions are the main propagators of this trend. Accordingly, those banks suffered also the largest losses, whereas the losses incurred by the smaller banks were relatively minor.

Overall, the facts about balance sheet weaknesses which prevail among the myths are, that both poor liquidity and risk management, mainly of the large institutions, resulted in substantial problems and losses. Troubles with off-balance sheet vehicles, which required liquidity injections and ultimately forced lower-quality assets back onto banks' balance sheets, will have put additional pressure on refinancing needs and write-downs.

To determine whether these factors are the main causes for the adverse impact of the financial crisis on the real economy, necessarily requires a more structural approach, which will be taken in the next chapter of this thesis. Nevertheless, the findings from individual bank data suggest that liquidity mismatches and heightened risk-taking are relevant catalysts, or even triggers, of the financial crisis 2007-2009.

Data Appendix

The dataset contains the CALL report data on all FDIC insured deposit taking institutions in the US. It covers both commercial banks under federal and state charter, including institutions which are not member of the FDIC, and savings banks and savings associations. It does not, however, cover branches and agencies of foreign bank offices (FBO's), which are significant suppliers of credit in the US. In the last decade they were responsible for up to 8,6% of total bank lending and up to 21.1% of C&I loans of all commercial banks in the last decade. At the peak in 2007, they held 15.6% of total assets. Foreign branches and agencies are mostly not FDIC insured, so they are not included in the dataset here. In particular, for the analysis of small business loans this poses a problem, as the actual lending figures might differ significantly when FBO's are included. Foreign banks' branches and agencies do file a so called FFIEC 002 form[15], which however does not cover most of the items analyzed here. In particular, the FFIEC 002 form only require insured institutions to provide data on small business lending. These, however, are already covered by the FDIC dataset. To get an impression of the

[15] See http://www.ffiec.gov/forms002.htm for all the series covered.

sensitivity of the results with respect to the inclusion of the FFIEC 002 data, I use the aggregate figures provide by the Federal Reserve[16] at annual frequency.

For the analysis of bank balance sheet characteristics like equity and liquidity ratios, and loan ratios, or return on equity, the inclusion of the data for foreign bank offices is problematic. Usually, these are highly depending on their foreign parents and in this sense, any of the measures under consideration are likely to be of limited information content, notwithstanding the restriction that only a very limited number of balance sheet items are reported. Hence, the concentration on all FDIC insured institutions in the US seems sensible in this context, and still conveys a fairly representative view of the banking sector as a whole.

The FDIC dataset includes some implausible data-points, which are removed from the dataset. These are institutions which exhibit zero or negative total assets, total loans, core equity or total risk based capital. Tables 1.4 and 1.5 presents a definition of the variables used in this paper, together with the corresponding FDIC variable names. The FDIC assigns a variable name to all positions in the CALL reports, which I refer to as *FDIC codes.* The dataset is assembled from the quarterly .zip files obtained by using the *download all available report options in all report categories* option on the *Statistics on Depository Institutions* (SDI) website http://www2.fdic.gov/sdi/[17]. Each of the .zip files contains all available reports and balance sheet items for all institutions in a given quarter in .csv format and a readme.html file, which contains the corresponding variable names. To merge all quarters into a panel, the FDIC certificate number (FDIC code: *cert*) serves as the unique identifier of an individual institution.

[16]Available at http://www.federalreserve.gov/releases/iba/

[17]The option can be found under *SDI Map, Definitions Data Download->Data Download->download all*

Variable	Definition
Total Loans	Net loans and leases minus leases. Net loans and leases are total loans and lease financing receivables minus unearned income and loan loss allowances. Leases are lease financing receivables, net of unearned income. (FDIC code: $lnlsnet - ls$)
C&I Loans	Commercial and industrial loans. Excludes all loans secured by real estate, loans to individuals, loans to depository institutions and foreign governments, loans to states and political subdivisions, and lease financing receivables. (FDIC code: *lnci*)
Small Loans	Small loans are the sum of all loans with a face value of 250,000 US$ or less. Small loans are reported for the following loan types: loans secured by nonfarm nonresidential properties, C&I loans to US addresses, loans secured by farmland, and loans to finance agricultural production. The data is available in annual frequency in Q2 of every year, and in quarterly frequency from Q1 2010. (FDIC code: $Lnrenr1 + Lnrenr2 + Lnci1 + Lnci2 + Lnreag1 + Lnreag2 + Lnag1 + Lnag2$)
Small C&I loans	Small C&I loans is the sum of C&I loans to US addresses with a face value of 250,000 US$ or less. The data is available in annual frequency in Q2 of every year, and in quarterly frequency from Q1 2010 onwards. (FDIC code: $Lnci1 + Lnci2$)
Cash balances	Total cash and balances due from depository institutions including both interest-bearing and non interest-bearing balances. (FDIC code: *chbal*)
Total Securities	Total investment securities (excludes securities held in trading accounts). The full implementation of FASB 115 became effective as of January 1, 1994. Beginning on that date, a portion of banks' securities portfolios are reported based upon fair (market) values; previously, all securities not held in trading accounts were reported at either amortized cost or the lower of cost or market value. (FDIC code: *sc*)

FDIC code pertains to the corresponding variable names in the FDIC dataset. See the Data Appendix for details. Definitions are from the *Statistics on Depository Institutions* (SDI) website (http://www2.fdic.gov/sdi/).

Table 1.4: Variable Definitions (Part I)

Variable	Definition
Government Obligations	The amortized cost and fair value of all U.S. Government agency obligations not held for trading. Excludes commercial mortgage-backed securities as of June 2009. (FDIC code: *scage*)
Non-Equity and Non-Deposit Liabilities	Total Liabilities minus total equity capital minus total deposits (FDIC code: $liab - dep$)
Core Equity	Total bank equity capital (includes preferred and common stock, surplus and undivided profits). (FDIC code: *eq*)
Total Risk Based Capital Ratio	Total risk based capital as a percent of risk-weighted assets as defined by the appropriate federal regulator for prompt corrective action during that time period. (FDIC code: *rbcrwaj*)
Ratio of Non-Current Loans to Loans	Total noncurrent loans and leases, Loans and leases 90 days or more past due plus loans in nonaccrual status, as a percent of gross loans and leases. (FDIC code: *nclnlsr*)
Ratio of Charge-Offs to Loans	Gross loan and lease financing receivable charge-offs, less gross recoveries (annualized), as a percentage of the year-to-date quarterly average of total loans and lease financing receivables. (FDIC code: *ntlnlsr*)
Net Interest Margin	Total interest income less total interest expense (annualized) as a percent of average earning assets. (FDIC code: *nimy*)
Return on Equity	Annualized net income as a percent of the year-to-date quarterly average of total equity on a consolidated basis. If retained earnings are negative, the return on equity is not reported. (FDIC code: *roe*)

FDIC code pertains to the corresponding variable names in the FDIC dataset. See the Data Appendix for details. Definitions are from the *Statistics on Depository Institutions* (SDI) website (http://www2.fdic.gov/sdi/).

Table 1.5: Variable Definitions (Part II)

Chapter 2

The Cross-Section of Bank Balance Sheets and Macroeconomic Factors of Aggregate Credit Supply

2.1 Introduction

What drives aggregate bank lending? During the financial crisis 2007-2009 in particular, this has been an issue of utmost relevance for policy makers and regulators. Despite the extensive rescue packages from the US Treasury department and the extraordinary low refinancing costs put in place by the Federal Reserve, aggregate bank lending in the US declined substantially. Bank balance sheet weaknesses, such as insufficient capital cushions as well as excessive risk taking, have been widely blamed for the apparent lack of banks' credit supply, spurring an overhaul of banking regulation. At the same time however, the macroeconomic environment deteriorated significantly. The disruption on the financial markets had adverse effects on the perceived risk in the financial sector, making it difficult for banks to refinance themselves. Further, expectations regarding future economic growth were strongly revised and concomitantly expected loan default rates rose. Naturally, this severely restricted banks in their capacity to supply credit, even though previously, bank balance sheets were under no sign of stress.

The aim of this paper is to shed light on the importance of bank balance sheet characteristics for banks' lending decisions *in the aggregate* and the dependency of those decisions on the state of the macroeconomy and financial market conditions.

Individual banks' lending decisions are made on the basis of their balance sheet characteristics, given current and expected economic conditions. Most empirical studies on the so-called bank lending channel, the effect of bank balance sheet characteristics on lending decisions, focus on the transmission mechanism of monetary policy. The effect of monetary policy on bank lending is then measured at the bank with average balance sheet characteristics, such as equity or liquidity. This study goes one step further by using a coherent aggregation procedure over the full distribution of individual banks to provide a measure for the importance of a wide range of balance sheet characteristics for *aggregate lending*. Even though my estimation is unrestricted in a sense that the setup does not preimpose the aggregate lending estimate to match observed aggregate lending in any way, the dynamics of aggregate lending can be matched with precision. This allows me to introduce a variance decomposition of aggregate lending - the taxonomy of bank balance sheet characteristics - by measuring how much of the variation in aggregate lending can be explained by the impact of differences in balance sheet characteristics (BCs) on lending decisions across banks. Whereas the variation in the balance sheet characteristics themselves cannot explain even a small part of the variance of aggregate lending, the bulk of the variance contribution stems from the variation in lending sensitivities with respect to the BCs, such as banks' core equity ratios. The second step is then to determine to which extent lending sensitivities are driven by macroeconomic and financial factors over time. A bank with a high core equity ratio for example has a greater capacity to absorb losses on its lending portfolio than a bank with low amounts of equity capital relative to its total assets. How severe this restriction is for their respective lending decisions, and eventually for observed aggregate bank lending, however, depends on common factors, such as expected economic growth, since with higher growth the default risks on banks' loan portfolios abate. The analysis here extends previous studies by looking at a more comprehensive set of macroeconomic (common) factors, such as expectations about future macroeconomic conditions and financial market risk.

The empirical literature on bank lending has established a variety of bank balance sheet variables which affect banks' lending supply conditional upon common macroeconomic factors, with a particular focus on monetary policy. Since bank lending *over time* will be also driven by demand, a fundamental identification problem of supply versus demand arises. To make progress on this issue, the literature has been utilizing bank-individual balance sheet data. The idea is that at *one point in time*, banks with stronger balance sheets have a higher credit supply capacity, and therefore the cross-sectional variation in observed lending growth identifies how sensitive lending decisions are with respect to various BCs. Implicitly, it is assumed that bank-individual characteristics pin down credit supply decisions, whereas the factors driving demand are common to at least a group of banks. Kashyap and Stein (2000) document the existence of a 'bank lending channel' of monetary policy in the US. When monetary policy tightens, banks with a higher *share of liquid assets* on their balance sheets can better compensate a loss of insured deposit financing by simply drawing down on their existing fungible securities. This effect is stronger for smaller banks, which are more dependent on deposits as a source of funding. Gambacorta and Mistrulli (2004) argue that, in addition, cross-sectional differences in risk-adjusted bank capital levels matter. Institutions with a stronger capital base can more easily tap the alternative markets for funding and regulatory restrictions on capital are less binding. Based on a sample of Italian banks, they find that banks with larger capital buffers can smooth lending better in response to both monetary policy and GDP shocks. Kishan and Opiela (2000, 2006) establish the relevance of a bank capital channel for the US and find asymmetric effects in the propagation of monetary policy. Contractionary policies are most effective on bank lending for low-capital banks, expansionary policies however are close to ineffective for this group. Ashcraft (2006) finds that the effect of Monetary Policy on bank lending in the US is quantitatively significant only for financially distressed banks, whereas being a member of a multi-bank holding can insulate against changes in interest rates for the average bank. In the light of financial innovation and the entailing change in banks business models, Altunbas et al. (2009) argue that the enormous growth in securitization in the Euro area has altered the liquidity, credit and maturity transformation role traditionally performed by its banks. As illiquid loans can be moved off the balance sheet, shortages in liquidity or capital can be overcome without affecting the supply of credit. They find evidence for a weaker influence of Monetary Policy on bank lending for banks with higher securitization activities. Altunbas et al. (2010) turn to the liability side and point to the perception of risk by financial markets as a criterion for banks capability to raise new funds, especially as the reliance on financing through capital markets has increased. Their results indicate that low-risk banks offer a larger amount of credit and can shield their lending better from monetary policy shocks as well as economic slowdowns. Accordingly, Cornett et al. (2011) present evidence that US banks with more stable sources of funding like core deposits and equity capital, continued to lend relative to other banks during the financial crisis 2007-2009. Ashcraft et al. (2010) emphasize the importance of the FHLB system as a lender of next to last resort for banks in the crisis and Ivashina and Scharfstein (2010) show that the spike in commercial and industrial loans following the collapse of Lehman Brothers was due to a simultaneous run by borrowers, who drew down on their existing credit lines.

The contribution of this paper is twofold. Firstly, it derives a taxonomy of bank balance sheet factors for *aggregate* bank lending for a wide range of BCs of interest, whereas most of the literature focuses on the effect of particular BCs in the transmission mechanism of monetary policy. At each point in time, the lending sensitivity with respect to the various BCs is measured. The cross-section is then aggregated up consistently to calculate the variance contribution of the BCs to aggregate bank sector lending over time. This allows a comparison of the impacts of the BCs relative to each other. In this sense, it sheds light on the balance sheet strengths and weaknesses which are constitutive for the banking system's capacity to supply credit before and during the recent financial crisis. Secondly, it looks at a broader set of macroeconomic factors, which are likely to influence lending sensitivities. Besides monetary policy and macroeconomic activity, the effects of *expected* macroeconomic conditions as well as financial market risks are analyzed. Indeed, expected rather than current macroeconomic conditions appear to play a significant role for the dynamics of aggregate lending decisions of small banks.

The next section presents the econometric model, the underlying dataset and the results of the cross-sectional estimation. Section 2.3 comprises the analysis of the relevant macroeconomic and financial factors and their impact on lending sensitivities. The final section concludes.

2.2 Bank Balance Sheet Characteristics and Aggregate Lending

To analyze how sensitive bank lending is to differences in banks' balance sheet characteristics at a given point in time, I pursue the method used by Kashyap and Stein (2000) and run the following repeated cross-section regression for every t separately:

$$gL_{i,t} = \mu_t + \sum_{j=1}^{J} \beta_{j,t} BC\left(j\right)_{i,t-1} + \varepsilon_{i,t} \tag{2.1}$$

with

$$\begin{aligned} BC_{t-1} \; = \; \big[\; & Eq_{t-1} \quad exc\,Tier2_{t-1} \quad Constr_{t-1} \quad Risk\,wt_{t-1} \quad NIM_{t-1} \\ & Due_{t-1} \quad Liq_{t-1} \quad Hold_t \quad Ext\,Fin_{t-1} \quad Sec\,Act_{t-1} \\ & Fed\,Funds_{t-1} \quad FHLB_{t-1} \quad NI\,Inc_{t-1} \quad UC_t \; \big] \end{aligned}$$

and $BC\left(j\right)$ the jth element of the vector of balance sheet characteristics BC. Table 2.1 contains a definitions of all the factors. Lending growth on the left hand side is net of interbank loans and loss allowances. The indices i and t denote the individual bank i and the quarterly time period t respectively.

Variable	Definition
$gL_{i,t}$	Quarterly loan growth rate. $gL_{i,t} = \frac{L_{i,t} - L_{i,t-1}}{L_{i,t-1}}$ where $L_{i,t}$ are an individual institution's loans and leases *net of loss allowances and interbank loans*. Interbank loans are defined as loans to commercial banks in the US, to US branches of foreign banks and other depository institutions in the US. (FDIC: $L_{i,t} = lnlsnet_t - lndepac_t$)
Eq	Core equity ratio. Bank equity capital (common stock, perpetual preferred stock, surplus and undivided profits) relative to total assets. (FDIC: $eq/asset$)
$exc\,Tier2$	Tier2 risk weighted capital ratio in excess of the regulatory minimum of 8%. (FDIC: $rbcrwaj - 8\%$)
$Constr$	Dummy for capital constrained institutions. All institutions with equity ratios below 6% or Tier2 capital ratios below 10%. (FDIC: $eq/asset * 100 < 6 \, or \, rbcrwaj < 10$)
$Risk\,wt$	Risk weighting. Risk weighted assets/total assets. (FDIC: $rwaj/asset$)
NIM	Net interest margin. Total interest income less total interest expense relative to earning assets. (FDIC: $nimy$)
Due	Ratio of past due and non-accrual assets to total assets. (FDIC: $(p3asset + p9asset + naasset)/lnlsnet$)
Liq	Ratio of liquid assets to total assets. Liquid assets are cash balances, trading assets, Fed Fund repos, and government-backed securities. (FDIC: $(chbal + trad + frepo + scus + scage + scmuni)/asset$)
$Hold$	Dummy for member of a Bank Holding. (FDIC: $namehcr$ exists)
$ExtFin$	External financing ratio. Ratio of non-equity, non-deposit financing to total liabilities. (FDIC:$(liabeq - dep - eq)/liabeq$)
$SecAct$	Securitization activity. Reported securitization of loans/total assets. (FDIC:$(szlnres + szlnhel + szlncrcd + szlauto + szlncon + szlnci + szlnoth)/asset$)
$Fed\,Funds$	Ratio of fed funds purchased and repurchase agreements to total assets. (FDIC: $frepp/asset$)
$FHLB$	Ratio of FHLB (Federal Housing Loan Bank System) advances to total assets. (FDIC: $othbfhlb/asset$)
$NI\,Inc$	Non-interest income relative to total assets. Non-interest income is defined as trading account gains + securities gains + additional non-interest income. (FDIC: $(iglsec + igltrad + idothnii)\,/asset$)
UC	Relative change in unused commitments: $\frac{unused\,loan\,commitments_t}{loans\,and\,leases_t} - \frac{unused\,loan\,commitments_{t-1}}{loans\,and\,leases_{t-1}}$. (FDIC: $\frac{ucln_t}{lnlsnet_t} - \frac{ucln_{t-1}}{lnlsnet_{t-1}}$)

All ratios and growth rates are expressed in %. FDIC gives the corresponding variable codes for the FDIC database.

Table 2.1: Definitions of Bank Characteristics (BC)

Hence, the OLS estimation results in a set of parameter estimates (μ, β) for each period t. All variables on the right hand side are lagged by one quarter to avoid a contemporaneous endogeneity of lending growth and balance sheet characteristics [1]. The resulting β -estimates represent the sensitivity of lending growth with respect to the corresponding BC at time t. The more of a restriction, for example, core equity is at a given point in time, the higher is the ceteris paribus effect of an additional unit of Eq on lending growth across individual banks, and therefore the greater the corresponding $\beta_{1,t}$. The lending sensitivities are likely to vary over time as the macroeconomic environment changes. The coefficients β_t are estimated in the cross-section and hence at a *given* state of the economy. Note that the β_t's are totally unrestricted in their movement over time, as there is no preimposed relationship between the cross-sections among the quarterly time periods t.

The quantitative effect for *aggregate* lending growth is derived by consistently summing up both sides of the equation to

$$\begin{aligned} gL_{agg,t} &= \mu_t + \beta_{2,t} \sum_i \omega_{i,t-1} Eq_{i,t-1} \\ &\quad + \sum_{j=3}^{J} \beta_{j,t} \sum_i \omega_{i,t-1} BC\left(j\right)_{i,t-1} + \sum_i \omega_{i,t-1} \varepsilon_{i,t} \end{aligned} \tag{2.2}$$

where the weights $\omega_{i,t-1} = \frac{L_{i,t-1}}{\sum_i L_{i,t-1}}$ are chosen to yield aggregate lending growth (within the respective size group) on the left hand side[2]. The *total impact on aggregate lending,* of say the core capital restriction, is then

$$\beta_{1,t} \sum_i \omega_{i,t-1} Eq_{i,t-1}$$

[1]See Kashyap and Stein (2000), Gambacorta and Mistrulli (2004), Ashcraft (2006), and Altunbas et al. (2009) among others. Given that banks de-facto practice a very timely balance sheet management (see for example Adrian and Shin (2010)), it seems realistic to assume that next quarter's lending decisions do not feed back to the current period's value of balance sheet characteristics. $Hold$ and is not lagged, as this dummy variable is to indicate whether a bank is a holding company in the current time period. UC is also a contemporaneous value, since it is supposed to capture the part in *current* lending growth, which is induced by a draw-down on unused loan commitments/credit lines from existing borrowers.

[2]

$$\begin{aligned} \sum_i \omega_{i,t-1} gL_{i,t} &= \sum_i \omega_{i,t-1} \frac{L_{i,t} - L_{i,t-1}}{L_{i,t-1}} = \sum_i \frac{L_{i,t-1}}{\sum_i L_{i,t-1}} \frac{L_{i,t} - L_{i,t-1}}{L_{i,t-1}} \\ &= \frac{\sum_i L_{i,t} - \sum_i L_{i,t-1}}{\sum_i L_{i,t-1}} \equiv gL_{agg,t} \end{aligned}$$

and hence consists of two parts: the sensitivity of lending growth with respect to core capital in period t measured by $\beta_{1,t}$, and the lending weighted level of core equity capital in the banking sector given by $\sum_i \omega_{i,t-1} Eq_{i,t-1}$, which will be referred to as the *bank sector level*. The tighter this restriction is in the cross-section, the larger is the corresponding β and thus the impact on aggregate lending. If the restriction is equally tight, but at higher levels of Eq, then the restriction is even more binding in an absolute sense and, hence, core equity capital is quantitatively even more important for lending decisions in the aggregate. The tighter the restriction, the stronger is the impact on aggregate lending.

Given the aggregate effects for each t, the first main question of this paper can be addressed, namely, how important are the BCs for aggregate lending dynamics? For this purpose, I calculate the share of the variance of aggregate lending which is explained by the total impact of $BC\,(j)$:

$$var\,share\,gL_{agg}\,(j) \equiv \frac{cov\left(gL_{agg,t}, \beta_{j,t} \sum_i \omega_{i,t-1} BC\,(j)_{i,t-1}\right)}{var\,(gL_{agg,t})} \tag{2.3}$$

with μ_t included as the case when $BC\,(j=0)_{i,t} = 1$ and $\beta_{0,t} = \mu_t \;\forall\, i, t$.
Since

$$\begin{aligned} var\,(gL_{agg,t}) &= cov\,(gL_{agg,t}, gL_{agg,t}) = \sum_{j=0}^{J} cov\left(gL_{agg,t}, \beta_{j,t} \sum_i \omega_{i,t-1} BC\,(j)_{i,t-1}\right) \\ &\quad + error \end{aligned}$$

it follows that[3]

$$\sum_j var\,share\,gL_{agg}\,(j) = \frac{\sum_j cov\left(gL_{agg,t}, \beta_{j,t} \sum_i \omega_{i,t-1} BC\,(j)_{i,t-1}\right)}{var\,(gL_{agg,t})} \approx 1$$

Hence, if the aggregate error term $\sum_i \omega_{i,t-1}\varepsilon_{i,t}$ is small (see section (2.2.3.2)) in all periods t, then the variance share in equation (2.3) can be interpreted as the percentage share of a balance sheet restriction j in the time variation in aggregate bank lending decisions.

[3] The approximate equality comes from the fact that
$var\,(gL_{agg,t}) = \sum_{j=0}^{J} cov\,(gL_{agg,t}, \beta_{j,t} \sum_i \omega_{i,t-1} BC\,(j)) + cov\,(gL_{agg,t}, \sum_i \omega_{i,t-1}\varepsilon_{i,t})$
and thus
$\sum_{j=0}^{J} var\,share\,gL_{agg}\,(j) = \frac{\sum_j cov\left(gL_{agg,t}, \beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1}\right)}{var(gL_{agg,t})} = 1 - \frac{cov\left(gL_{agg,t}, \sum_i \omega_{i,t-1}\varepsilon_{i,t}\right)}{var(gL_{agg,t})}$.
Given that $\frac{cov\left(gL_{agg,t}, \sum_i \omega_{i,t-1}\varepsilon_{i,t}\right)}{var(gL_{agg,t})}$ is small, as shown below, it follows that $\sum_{j=0}^{J} var\,share\,gL_{agg}\,(j) \approx 1$.

2.2.1 Data

The data for this analysis is taken from the quarterly US CALL reports from Q1 2002 until Q2 2010 for all FDIC insured institutions as published on the FDIC website[4]. The raw data features some outliers and implausible values, which have to be excluded in order to avoid undesirable biases. Details can be found in the Appendix. Starting from an average of around 8,700 observations, it reduces the dataset to around 7,750 observations on average per quarter[5].

The dataset is divided into two size groups, the 95% quantile and the top 5% of the size distribution[6]. For each of the size groups, the regressions are run separately, as small banks and large banks are likely to differ in their respective lending sensitivities for three reasons[7]. Firstly, they have a different level of access to capital market funding for both equity and debt[8]. As Figure 2.1 shows, the share of external funding in total liabilities is significantly higher, while non-equity and non-deposit financing of the small banks is almost entirely raised through Fed Funds and FHLB advances. In addition, Table 2.2 indicates that a far bigger share of large banks is engaged in securitization activities (over 11% of large banks compared with less than 1% of small banks prior to Q3 2008) and those activities on average amount to a larger share of total assets (12% compared to 7% for the smaller institutions before the crisis, and 11% compared to 6% thereafter). This can provide a greater flexibility for issuing new loans, even in cases when capital and liquidity ratios are not very high (Altunbas et al. (2009)). Secondly, their business models have become increasingly different. Large banks tend to have larger Investment Banking departments. In good times, this can substantially contribute to their revenue and therefore increase lending capacity, whereas during downturns this effect can work strongly into the opposite direction. Thirdly, large

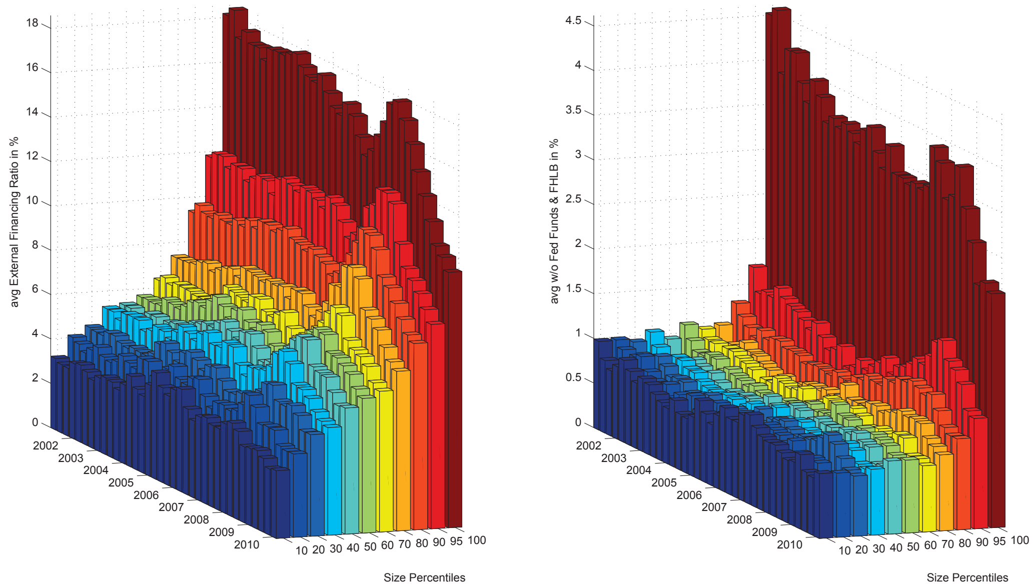
[4]The data is publicly available for download at http://www2.fdic.gov/sdi/. The database does not include Offices and Branches of foreign banks. See the Appendix for a discussion.

[5]All calculated statistics, time series and results in the paper are based upon this stratified dataset.

[6]This yields an average of around 370 observations per quarter for the large banks group, which enables sufficiently precise estimates in the cross-sectional econometric analysis. The upper 5% of the size distribution are responsible for more than 80% of aggregate lending. As the focus of this analysis is on the relevance of cross-sectional restrictions for *aggregate* lending, a further slicing of the group of small banks has little effect, as in any case it represents less than a quarter of aggregate lending already. The size groups are recalculated at every quarter.

[7]As the differences in size are likely to affect the lending sensitivities itself rather than lending growth directly, it seems appropriate to divide the dataset into different groups. Furthermore, the effect the 'size effect' on lending growth is potentially highly non-linear. Consequently, simply adding total assets as a right hand side variable may not take account for the compounded non-proportional effect of size.

[8]A better access to capital markets can reflect a size and cost advantage regarding capital increases and bond issuance only, but may also include a 'too big to fail' effect.



The 3D bars show the average External Financing Ratio (non-equity and non-deposit financing relative to total liabilities) for institutions within the given size percentile interval. The utmost left bar thus shows the average External Financing Ratio of the smallest 10% of all institutions for each quarter from Q1 2001 until Q3 2009. The bar at the 20 percentile represents the average of all institutions which are among the 20% largest institutions, but are larger than the 10% smallest banks. The right graph plots the External Financing Ratio without Fed Funds and FHLB liabilities.

Figure 2.1: External Financing Ratios

and small banks have a different costumer base. *Small Loans* in Table 2.2 denote the value weighted share of small loans[9], indicating that large banks typically also grant larger loans. Assuming that larger loans on average are assigned to larger firms or richer individuals, a differential response in demand across bank size could occur, as larger firms, for example, are less dependent on bank credit and may also be able to better weather economic difficulties, as they are more diversified.

[9]Small loans are defined here as loans with a value of $250k or less. This includes loans secured by nonfarm nonresidential properties, C&I loans to US addressees, loan secured by farmland and loans to finance agricultural production. The share of small loans is calculated as small loans relative to the total amount of loans in the corresponding categories.

2.2.2 Balance Sheet Characteristics

As the aim of this paper is to analyze a comprehensive set of balance sheet characteristics, both well-established characteristics from the literature and a number of additional variables are employed, to capture the specifics of the recent crisis. The right hand side variables in equation (2.1) can be subsumed into 5 groups:

1. Bank capital: Eq, $excTier2$, $Constr$
2. Risk: $Risk\,wt$, NIM, Due
3. Liquidity and Financing: Liq, $Hold$, $Ext\,Fin$, $Sec\,Act$, $Fed\,Funds$, $FHLB$
4. Non-interest income: $NI\,Inc$
5. 'Demand' factors: μ, UC

Table 2.2 provides some summary statistics. *Bank capital* here is comprised of both, the core equity ratio (Eq) and the excess Tier2 capital ratio ($excTier2$), which reflect different types of capital reserves. Whereas core equity is a measure for the pure loss absorbing capacity of a bank, the Tier2 capital ratio is risk weighted to make the capital reserves comparable among institutions with different risk profiles[10]. Foremost, the Tier2 capital ratio is a regulatory restriction. As the time-constant regulatory risk weights may not reflect the perception of risk of a bank, especially in a changing macroeconomic environment, Tier2 capital cannot reflect the total effect of the capital restriction. Core equity, particularly in crisis times, contains additional valuable information on how binding the equity capital restriction is for lending decisions. Getting very close to the constraints can severely limit an institution's capacity to obtain funding, and it may, in the worst case, lead to regulatory actions, such as a complete shut-down of a distressed bank's lending business. Once banks come very close to the constraint, the expected costs

[10] In the time period under consideration, US banks were regulated according to the BASEL I framework, under which banks have to hold at least 8% Tier2 capital relative to their risk weighted assets. The excess Tier2 capital ratio ($excTier2$) is simply the Tier2 risk weighted capital ratio minus the regulatory minimum of 8 %. Under Basel I, the risk weights are constant and fixed for a given asset class. Loans receive the full risk weights whereas for example Treasury Bills and loan commitments carry a zero weighting. Tier 2 capital equals common capital stock plus qualified perpetual preferred stock (= Tier 1 capital) plus supplementary capital, which is categorized as undisclosed reserves, revaluation reserves, general provisions, hybrid instruments and subordinated term debt. For details see http://www.bis.org/publ/bcbsc111.pdf

In addition, US banking regulation imposes a minimum core equity ratio (Eq). The effective minimum depends on a banks CAMELS (*C*apital Adequacy, *A*sset Quality, *M*anagement, *E*arnings, *L*iquidity, and *S*ensitivity to Market Risk) rating, which is an undisclosed rating conducted by the responsible regulator. Banks with the best possible rating of 1 required a minimum core capital ratio of at least 4% until Q4 2010.

are likely to explode[11]. Accordingly, most bank balance sheets exhibit capital buffers[12] to insure against such cases. To take account for extreme cases, I use a dummy ($Constr$) for institutions which have a Tier 2 capital ratio below 10% ($excTier2 < 2\%$) or a core equity ratio below 6%.

The second group of variables captures the riskiness of a bank's loan portfolio. The literature so far has emphasized the implications of risk taking on the refinancing ability of a financial institution and therefore has analyzed the effects of perceived risk by the capital markets on lending activity (Altunbas et al. (2010)). The analysis here, however, is concerned with the taxonomy of bank balance sheet characteristics as a first step, and therefore focuses on the risk of an *institution's* asset portfolio. To capture at least some of the effect of *risk* on credit supply capacity, three variables serve as proxies: The Basel I risk weight ($Risk\,wt$), the net interest margin (NIM), and the amount of over-due loans relative to total gross loans (Due). Whereas Due is rather an ex-post measure of risk, both $Risk\,wt$ and NIM are arguably more forward looking. Even though the Basel I risk weight cannot distinguish ex-ante between more and less risky loans or securities, it still provides relevant information about the riskiness of an institution's business model. For example, if an institution's assets consist only of Treasury Bills, then the risk factor would be equal to zero, whereas if the asset side is comprised only by loans, this factor equals one. The idea behind the net interest margin is, that on average banks which take on loans with a higher perceived risk, should charge a higher markup on their loan rates to cover the relatively higher expected costs of loan defaults.

In addition to the well-established characteristics like Liq (Kashyap and Stein (2000))[13], $Hold$ (Ashcraft (2006)) and $Sec\,Act$ (Altunbas et al. (2009)), which measure the effects of liquidity and financing on credit supply, three more variables are introduced. $Ext\,Fin$, on the one hand, is consistent with the idea that banks with better access to capital markets have ceteris paribus more flexibility in taking on new loans. A higher ratio of non-equity and non-deposit financing is taken as a signal for better access to external funding sources, given that deposit and equity financing is more difficult to obtain and is likely to be more expensive.

[11] see van den Heuvel (2007)

[12] This is also an outcome of theoretical models with uncertainty in default rates or loan demand (Zicchino (2006), Van den Heuvel (2007)). Banks hold a capital buffer in the optimum as an insurance against a rise in default rates, or as a buffer for unexpected spikes in loan demand.

[13] The liquidity ratio Liq is defined slightly differently. Here, only cash balances, the trading account, Fed Fund repos and government-backed securities are considered liquid assets. Usually, the literature uses total security holdings and not just government-backed securities in addition to the aforementioned components. For the period under consideration, especially from 2008 until 2009, this definition appears to be too wide, since most securitized loans and mortgages were hardly salable.

	Pre-Crisis (Q1 '01 - Q2 '08)		Crisis (Q3 '08 - Q2 '10)			Pre-Crisis (Q1 '01 - Q2 '08)		Crisis (Q3 '08 - Q2 '10)	
	Small	Top 5%	Small	Top 5%		Small	Top 5%	Small	Top 5%
gL	2.6	2.6	1.1	-0.15	$Ext\,Fin$	6.5	15.9	6.7	13.7
	(6.3)	(5.6)	(5.9)	(5.9)		(6.7)	(9.5)	(6.5)	(8.4)
gL_{agg}	2.6	2.3	0.49	-0.21	$Sec\,act$	7.3	12.2	5.8	10.6
$Small\,Loans$	42.5	12.3	33.5	9.9		(18.1)	(26.7)	(17.1)	(20.4)
Eq	10.6	9.3	10.7	9.6		0.546	11.5	1.0	8.5
	(3.5)	(2.8)	(3.7)	(2.7)	$Fed\,Funds$	3.1	5.8	2.9	4.6
$Exc\,Tier2$	9.2	5.6	8.8	5.7		(3.2)	(4.5)	(3.0)	(3.7)
	(8.2)	(5.2)	(7.9)	(5.0)		36.9	80.6	34.8	79.0
$Constr$	1.9	3.7	4.0	7.4	$FHLB$	7.3	9.5	7.4	8.2
$Risk\,wt$	67.8	71.8	69.5	73.7		(6.0)	(7.6)	(5.7)	(6.7)
	(13.3)	(13.4)	(12.9)	(12.8)		60.6	86.0	65.3	89.2
NIM	4.1	3.7	3.8	3.4	$NI\,Inc$	0.264	0.561	0.215	0.407
	(0.9)	(0.9)	(0.8)	(0.9)		(0.6)	(1.0)	(0.6)	(0.9)
Due	1.4	1.1	2.7	3.4	UC	0.042	0.091	-0.393	-0.526
	(1.3)	(1.0)	(2.6)	(2.8)		(4.3)	(5.2)	(3.8)	(4.5)
Liq	45.4	40.2	41.3	35.5	$rel\,to\,Loans$	16.5	36.8	13.9	29.7
	(26.0)	(22.8)	(25.2)	(20.5)	$No\,Obs$	199189	10500	53620	2825
$Hold$	72.5	74.3	73.8	76.3	$p.Q.$	7114	375	6703	353

All values are expressed in % per quarter. Variable definitions can be found in Table 2.1. All summary statistics and size cut-offs are calculated based upon the stratified sample described in section 2.2.1 as arithmetic means across institutions and quarters. The numbers in brackets are the corresponding standard deviations. *Small* denotes all institutions within the lower 95% of the total asset distribution, while *Top 5%* comprises the upper 5% of the total asset distribution in the sample. *Small Loans* is the value weighted share of loans smaller than $250k in total loans. *Constr* and *Hold* are the average percentage of institutions which are capital constrained or belong to a Multi-Bank Holding, respectively. *UC rel to Loans* takes the total value of unused commitments for each institution and divides it by the value of total net loans (net of charge-offs). The statistics for the *Sec act*, *Fed Funds* and *FHLB* are calculated conditional on the observations being non-zero. Correspondingly, *Obs p.Q.* are the average number of non-zero observations per quarter. The last two lines ($No\,Obs$ and *p.Q.*) provide the total number of observations and the average number of observations per quarter within the respective the time period and size group.

Table 2.2: Summary Statistics

Both $Fed\,Funds$ and $FHLB$ are owed to the extraordinary liquidity shortages during the recent crisis. As Fed Funds carry a stigma as a source of funding (Furfine (2001)), because other forms of financing like unsecured interbank lending are cheaper, higher ratios of funding through Fed Funds, of which the Federal

Reserve has supplied enormous amounts, signal a relative inability to obtain funds through market sources. But also the Federal Housing Loan Bank (FHLB) system served as a significant provider of liquidity for banks, during and before the crisis (see Ashcraft et al. (2010)). $FedFunds$ and $FHLB$ together make up the bulk of external financing for small banks (see Figure 2.1). For a large number of small institutions it is actually the only source of external financing such that, for the group of small institutions, a colinearity problem among the right hand side variables arises. As a consequence, $Ext\,Fin$ is excluded as an explanatory variable for this group.

Non-interest income has become an increasingly important source of revenue for some banks. A higher revenue aside the traditional lending business can provide additional capacities for lending, and therefore it is a relevant balance sheet characteristic for lending decisions.

A significant part of the demand effect on credit growth is likely to be common across banks and not dependent on individual-specific bank characteristics. Therefore it should be picked up by the constant μ. The constant, however, is relative to what can be explained by the BCs. Hence, it can be interpreted as an 'excess demand' effect. According to Ivashina and Scharfstein (2010), unused commitments are however one individual-specific characteristic which has driven loan growth during the recent crisis. Existing credit lines or unused loan commitments were used by creditors[14] to bridge possible liquidity gaps, which partly forced banks to supply credit in a situation where an expansion of their loan portfolio was not optimal. To take account for this effect as far as possible, I use the change in unused loan commitments relative to total loans (UC) as an explanatory variable. If commitments grow steadily with granted loans, then UC should be close to zero. However, when the value of loans grows because commitments are exploited, then this factor becomes highly negative and can pick up cross-sectional variation in lending growth. On average, UC has indeed been lower during the crisis, but there are large standard errors associated with these values. Relative to total loans, large banks exhibit far higher rates of unused commitments, which could reflect loan commitments to off-balance sheet vehicles.

2.2.3 Results - Cross Section

The taxonomy of bank balance sheet characteristics for aggregate lending is summarized in tables 2.3 and 2.4. Overall, only a few BCs provide a significant quantitative contribution to aggregate lending dynamics. The BCs with the highest contributions among the small institutions are the core equity ratio Eq and

[14] Large banks in particular had to provide large amounts of back-stop liquidity for their off-balance sheet vehicles. See Brunnermeier (2009).

$Risk\,wt$, whereas the external financing ratio $Ext\,Fin$, and also Eq, are responsible for most of the variation in large banks aggregate lending. Figure 2.2 visualizes the total contributions and betas versus the aggregate lending dynamics within the respective size groups over time.

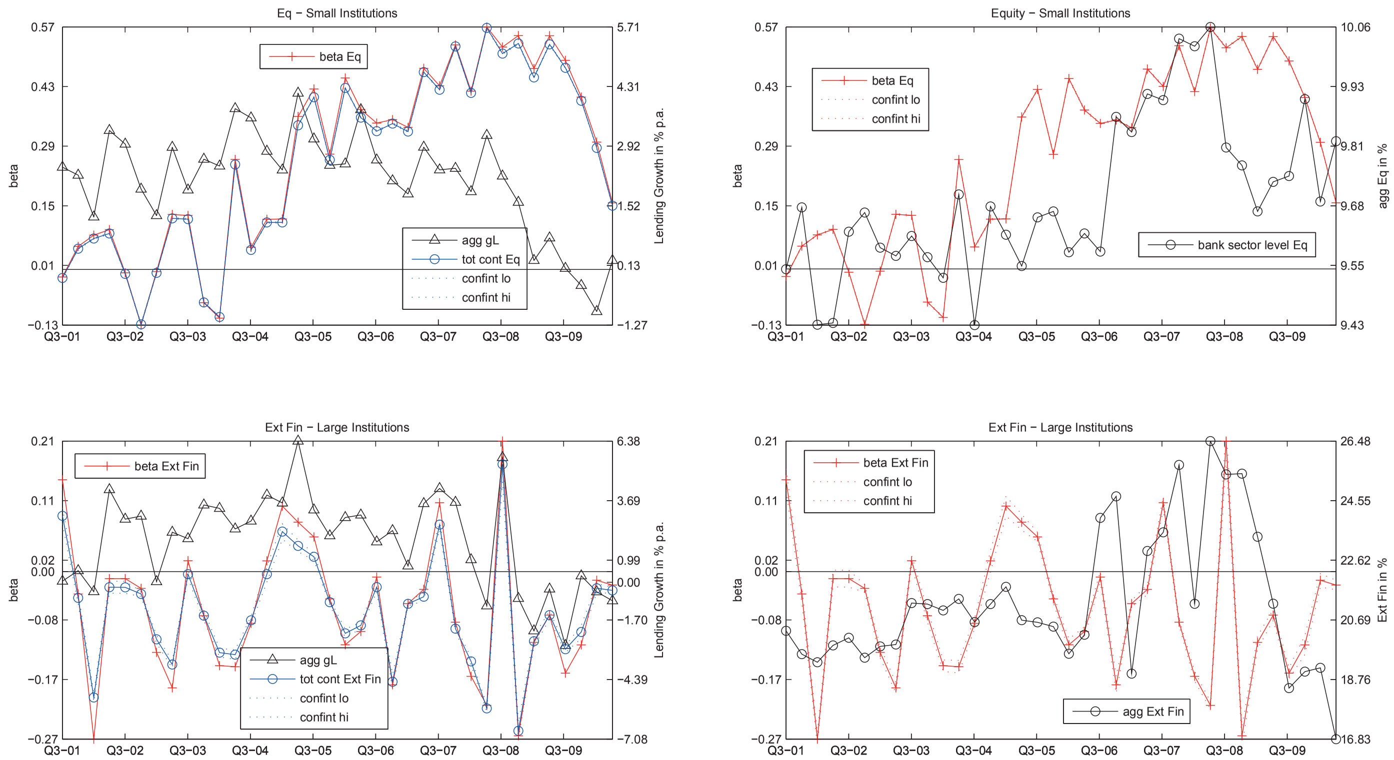
A first observation to be noted is the strong correlation between the estimated betas and the total effect of the BCs on aggregate lending. This effectively means that the variation of the total lending contributions is driven by varying lending sensitivities, and not by the variation in the BCs. Hence, the decrease in the total effect of the core equity ratio starting in Q1 2009, does not mean that banking sector core equity ratios have decreased, but it indicates a relaxation of the observed lending sensitivity with respect to core equity ratios. Generally, for the BCs[15] the estimated total impacts on aggregate lending are almost entirely driven by the changes in the respective lending sensitivities, as shown in tables 2.3 and 2.4, where $var\,share\,beta$ and $var\,share\,BC$ are the first order approximations of the variance contributions of the beta and the banking sector levels to the total impact of the corresponding BC, respectively. This is a pertinent point, as it implies that banks are actively forming their lending decisions on the basis of their balance sheet strengths and are not just mechanically reacting to changes in their BCs. Moreover, since the betas and the corresponding banking sector levels move fairly independently of each other over time (the correlations are presented in lines $corr\,beta - BC$), banks must be reacting to changes in other time-varying exogenous factors, like macroeconomic activity or financial market conditions.

2.2.3.1 Small Institutions

As depicted in Figure 2.2, the banking sector level of Eq was increasing until Q2 2008, and then experienced a decline of 0.4 percentage points until Q1 2009. Through this period, the bindingness of the equity constraint, as measured by the lending sensitivity $beta\,Eq$, remained high at a value of around 0.5, which translates into a 0.5 percentage point higher lending growth for banks with a ceteris paribus 1% higher core equity ratio! The amount of core equity hence was crucial for small banks lending decisions.

$Risk\,wt$ has a constantly positive impact in the pre-crisis period (mean of 5.31% p.Q.). However, it contributes strongly negatively to the dynamics of lending growth. A high and positive $Risk\,wt$ beta results in periods where banks with already risky business models take on relatively more loans. This relationship is

[15] The only exceptions are the ratio of over-due loan to total loans (Due) and the relative change in unused commitments (UC), which is just a control for changes in lending growth which are independent of any balance sheet considerations. The lending sensitivities with respect to Due are more stable than Due itself, which suggests that the ratio of over-due loans has a very direct impact on lending decisions.



Plotted in the left-hand-side graphs are the estimated betas $\beta_{j,t}$ (red, left scale) and the total contribution $\beta_{j,t} \sum_i \omega_{i,t-1} BC\left(j\right)_{i,t-1}$ (blue, right scale) of the corresponding balance sheet characteristic to aggregate lending growth, together with the within size-group aggregate lending growth itself (black, right scale).The right-hand-side graphs depict the estimated betas $\beta_{j,t}$(red, left scale) and the bank sector levels $\sum_i \omega_{i,t-1} BC\left(j\right)_{i,t-1}$. The heteroskedasticity robust 95% confidence intervals (for the small institutions the intervals are very small) indicated by the dotted lines correspond to the total lending growth contributions for the left-hand-side graphs and to the beta estimates in the right-hand-side plots. The solid flat black line indicates a zero beta and thus corresponds to the left hand-side vertical axis.

Figure 2.2: Contribution of Eq (Small Banks) and $Ext\,Fin$ (Large Banks) to Within-Size Group Aggregate Lending

	Pre-Crisis - Small Institutions														
	gL agg	*Const*	*Eq*	*Exc Tier2*	*Constr*	*Risk wt*	*NIM*	*Due*	*Liq*	*Hold*	*Sec act*	*Fed Funds*	*FHLB*	*NI Inc*	*UC*
mean (% p.Q.)	2.60	-1.31	2.08	-0.348	0.002	5.31	-1.25	-1.01	0.205	-0.910	-0.002	-0.015	-0.164	0.119	-0.007
min (% p.Q.)	1.26	-4.00	-1.25	-1.02	-0.047	2.59	-2.61	-1.49	-0.552	-1.57	-0.011	-0.154	-0.396	-0.348	-0.237
max (% p.Q.)	4.16	1.15	5.69	0.371	0.045	9.73	-0.196	-0.700	0.837	-0.511	0.015	0.154	-0.000	0.512	0.366
var share beta			0.984	1.02	1.01	1.06	0.996	0.601	1.00	1.02	0.928	1.00	1.07	0.978	0.014
var share BC			0.016	-0.019	-0.013	-0.059	0.004	0.399	-0.003	-0.025	0.072	-0.002	-0.069	0.022	0.986
corr beta - BC			0.675	0.632	-0.412	-0.831	-0.009	0.436	-0.128	0.426	-0.049	0.119	0.553	-0.329	0.474
agg g_L var cont	100.00	65.17	64.79	-11.84	-0.060	-70.55	19.28	3.94	10.71	20.93	-0.089	-3.40	-2.28	2.86	4.49
	Crisis - Small Institutions														
mean (% p.Q.)	0.479	1.43	4.17	-0.712	-0.020	0.069	-1.76	-1.64	-0.008	-0.870	-0.001	-0.065	-0.157	0.062	0.190
min (% p.Q.)	-0.954	-0.700	1.52	-1.00	-0.046	-1.46	-2.79	-2.05	-0.484	-1.05	-0.001	-0.176	-0.292	-0.202	-0.038
max (% p.Q.)	2.22	3.76	5.32	-0.048	0.023	2.01	-1.08	-1.05	0.389	-0.592	0.001	0.051	0.057	0.411	0.413
var share beta			1.00	1.04	1.03	0.963	0.987	0.095	1.00	0.996	0.716	1.04	1.17	1.06	0.020
var share BC			-0.003	-0.041	-0.033	0.037	0.013	0.905	-0.001	0.004	0.284	-0.036	-0.168	-0.059	0.980
corr beta - BC			-0.184	0.833	-0.567	0.389	-0.351	0.332	-0.046	-0.239	-0.372	0.804	0.751	-0.502	0.668
agg g_L var cont	100.00	-113	74.72	-8.82	2.24	101	-4.92	5.87	17.26	8.04	-0.021	4.88	2.18	2.37	10.98

Summarized are the results of the repeated cross-section estimation (2.2) for the class of small banks as defined in section 2.2.1. *mean* is the time-series mean of $\beta_{j,t}\sum_i \omega_{i,t-1}BC\left(j\right)_{i,t-1}$, and *min* and *max* are the corresponding minimum and maximum values. *var share beta* and *var share BC* are the first-order approximations of the variance contribution of $\beta_{j,t}$ and $\sum_i \omega_{i,t-1}BC\left(j\right)_{i,t-1}$ respectively, to the total effect $\beta_{j,t}\sum_i \omega_{i,t-1}BC\left(j\right)_{i,t-1}$. Details concerning the approximation are provided in the Appendix. The time-series correlation between the estimated coefficients $\beta_{j,t}$ and the banking sector levels $\sum_i \omega_{i,t-1}BC\left(j\right)_{i,t-1}$ is given by $corr\, beta - BC$. $var\, cont\, agg\, gL$ is the variance contribution of $\beta_{j,t}\sum_i \omega_{i,t-1}BC\left(j\right)_{i,t-1}$ to aggregate lending $gL_{agg,t}$, as explicated in equation (2.3) expressed in percent. The column $gL\, agg$ provides the respective statistics for the within size-group aggregate lending growth.

Table 2.3: The Taxonomy of Bank Balance Sheet Characteristics - Small Institutions

	gL agg	*Const*	*Eq*	*Exc Tier2*	*Constr*	*Risk wt*	*NIM*	*Due*	*Liq*	*Hold*	*Ext Fin*	*Sec act*	*Fed Funds*	*FHLB*	*NI Inc*	*UC*
							Pre-Crisis - Large Institutions									
mean (% p.Q.)	2.43	1.85	-1.19	0.366	0.011	2.22	0.565	-1.03	-0.091	0.095	-1.22	0.062	0.144	0.380	0.067	-0.056
min (% p.Q.)	-1.06	-7.23	-6.06	-0.865	-0.121	-5.72	-5.79	-2.19	-1.36	-1.69	-5.69	-0.505	-1.24	-0.460	-1.77	-1.09
max (% p.Q.)	6.38	9.35	5.63	2.12	0.194	8.86	4.54	-0.020	1.94	2.58	3.00	0.947	2.52	1.92	1.92	1.37
var share beta			0.997	1.01	1.03	0.997	0.996	0.801	1.00	0.998	0.993	0.987	0.978	0.921	1.02	-0.004
var share BC			0.003	-0.005	-0.032	0.003	0.004	0.199	-0.001	0.002	0.007	0.013	0.022	0.079	-0.024	1.00
corr beta - BC			-0.264	-0.175	-0.359	0.323	0.319	-0.481	0.068	-0.619	-0.077	0.221	0.347	0.383	-0.309	-0.121
agg g_ L var cont	100.00	67.47	-57.48	8.86	-0.178	-16.56	22.72	7.00	-7.71	3.09	64.37	-0.516	-25.97	-14.63	6.71	0.495
							Crisis - Large Institutions									
mean (% p.Q.)	-0.176	4.31	-1.19	0.628	0.004	0.721	-0.493	-2.07	-0.460	-1.05	-1.43	0.059	0.454	0.274	0.124	0.216
min (% p.Q.)	-2.85	-5.07	-4.23	-1.37	-0.054	-2.73	-4.10	-3.69	-2.01	-2.23	-6.71	-0.542	-2.51	-1.35	-0.485	-0.430
max (% p.Q.)	5.63	11.50	1.95	4.13	0.102	9.36	1.73	-1.21	1.39	0.902	5.33	0.713	2.94	1.29	0.590	1.02
var share beta			0.998	0.907	0.886	0.985	0.999	0.168	1.00	0.999	1.00	0.892	0.999	0.990	1.11	-0.011
var share BC			-0.007	0.544	0.645	0.510	0.185	0.286	0.316	-0.752	0.092	0.258	-0.078	0.151	-0.745	-0.291
corr beta - BC			-0.007	0.544	0.645	0.510	0.185	0.286	0.316	-0.752	0.092	0.258	-0.078	0.151	-0.745	-0.291
agg g_ L var cont	100.00	89.40	-7.06	1.15	1.39	2.12	-59.42	3.69	16.74	6.12	103	-7.50	-45.82	-23.54	7.32	-4.74

Summarized are the results of the repeated cross-section estimation (2.2) for the 5% largest banks, using the *conservative aggregation method* as described in the Appendix. *mean* is the time-series mean of $\beta_{j,t} \sum_i \omega_{i,t-1} BC\,(j)_{i,t-1}$, and *min* and *max* are the corresponding minimum and maximum values. *var share beta* and *var share BC* are the first-order approximations of the variance contribution of $\beta_{j,t}$ and $\sum_i \omega_{i,t-1} BC\,(j)_{i,t-1}$ respectively, to the total effect $\beta_{j,t} \sum_i \omega_{i,t-1} BC\,(j)_{i,t-1}$. Details concerning the approximation are provided in the Appendix. The time-series correlation between the estimated coefficients $\beta_{j,t}$ and the banking sector levels $\sum_i \omega_{i,t-1} BC\,(j)_{i,t-1}$ is given by $corr\,beta - BC$. $var\,cont\,agg\,gL$ is the variance contribution of $\beta_{j,t} \sum_i \omega_{i,t-1} BC\,(j)_{i,t-1}$ to aggregate lending $gL_{agg,t}$, as explicated in equation (2.3) expressed in percent. The column $gL\,agg$ provides the respective statistics for the within size-group aggregate lending growth.

Table 2.4: The Taxonomy of Bank Balance Sheet Characteristics - Large Institutions

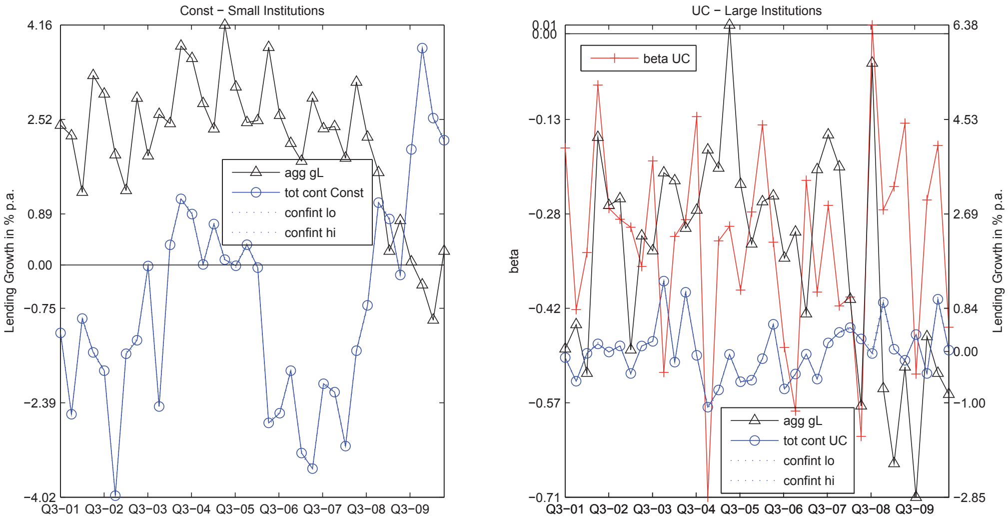
even stronger at times when lending growth is weaker, and the effect is strongly positive until Q3 2008. In essence, additional risk taking by banks with already high risk weights contributed to aggregate lending, especially in periods when more conservative banks cut back their lending activities. The banking sector level of $Risk\,wt$ increased from just under 70% to more than 76%, equivalent to a shift from absolutely save assets, like Treasuries, to risky loans, amounting to 6% of total asset, which translates into a possible increase in lending of around $400bn!

Hence, for the group of small banks, the pre-crisis period can be characterized as a period of additional risk-taking, both of banks with already risky balance sheets and of solidly financed institutions with high equity ratios.

With the outbreak of the crisis, this trend sharply reversed. Risk weights fell by more than 4 percentage points and additional risk taking vanished. Starting from Q3 2009, the equity restriction also became less binding, a year after the outbreak and after the disruptive effects of the crisis had abated.

Each effect can explain almost the entire variation in crisis lending dynamics. The reciprocal is picked up by the common effect μ. Assuming that it captures the 'excess demand' effect, Figure 2.3 suggests that the effect was negative in the two years leading up to the crisis and grew quickly to around 3% p.Q. by Q3 2009, implying a change from excess supply to excess demand of loans. Other balance sheet characteristics do not seem to drive a substantial part of aggregate lending dynamics. The absolute impact of Liq is small (max 0.84% p.Q. pre-crisis and max 0.39% p.Q. afterwards), even during the crisis. The extraordinary measures of liquidity provision by the Fed appear to have been effective in this respect, as also $Fed\,Funds$ and $FHLB$ do not pose a restriction to lending decisions in the aggregate. UC, at least for the group of small institutions, neither plays a noteworthy role nor exhibits a noticeable pattern. The two other risk proxies are more relevant. Both NIM and Due exert a negative effect on aggregate lending of slightly above 1% pre-crisis and 1.5% afterwards, in line with the expectation of a more limited credit supply capacity, when the asset portfolio is perceived as relatively more risky; both ex-ante and ex-post. In the pre-crisis period, the total effect of the net interest margin could explain roughly 20% of the variation in aggregate lending of small banks.

The majority of the smaller banks, in the sample between 55% and 62% (uniformly increasing over time), are state-chartered and thus their lending business is constrained to the state they are registered in. As during the crisis, some states have been hit harder by the crisis than others, imposing the same common demand effect across all states may be too restrictive. In particular, this may lead to an overstating of the impacts of some bank characteristics on aggregate lending, whereas these effects are really due to different state demand effects. For that matter, I introduce a full set of state-dummies into regression (2.1), instead of



Plotted are the estimated betas $\beta_{j,t}$ (red) and the total contribution $\beta_{j,t}\sum_i \omega_{i,t-1} BC\,(j)_{i,t-1}$ (blue) of the corresponding balance sheet characteristic to aggregate lending growth, together with aggregate lending growth itself (black) over time. The estimated betas $\beta_{j,t}$ for the right graph are measured on the left scale. The heteroskedasticity robust 95% confidence intervals (intervals are very small), indicated by the dotted lines, correspond to the total lending growth contributions.

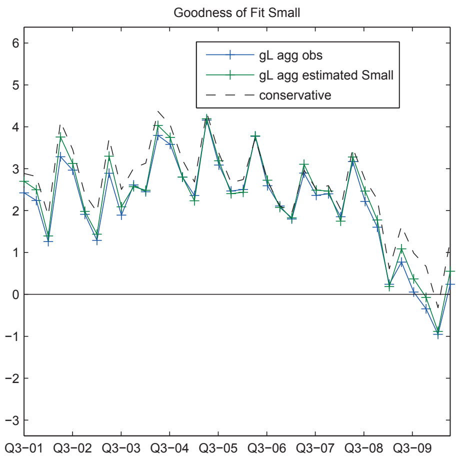
Figure 2.3: Contribution of *Const* (Small Institutions) and *UC* (Large Institutions) to Within-Size Group Aggregate Lending

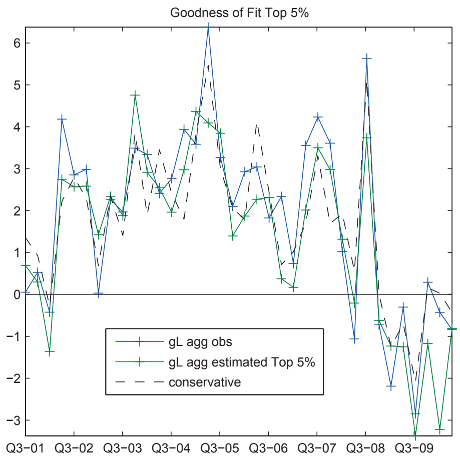
just one global constant μ. Table 2.8 in the Appendix, however, demonstrates that state-specific demand effects do not decisively alter the results. Slightly more of the variation in aggregate lending is now picked up by the state dummies, as compared to the single constant term μ, but the variance contributions of the BCs are very similar. Only the negative contribution of *Risk wt* is even stronger in the pre-crisis period now, whereas the post-crisis contribution is smaller, though still large. Some part of what is reflected by the variation in Basel I risk weights is obviously due to differences across states. Nevertheless, this does not affect the more general result that core equity ratios and *Risk wt* are the bank characteristics, which are driving most of the variation in lending growth.

Unlike argued in Gambacorta and Mistrulli (2004), the risk-weighted equity ratio is by far less relevant than the actual core equity ratio. This confirms the view that risk weights are not very precise measures of the actual underlying risks perceived by the banks themselves. Core equity, as a pure measure of the loss-absorbing capacity of a bank, seems to be much more relevant for banks' lending decisions in the aggregate.

2.2.3.2 Large Institutions and Robustness Issues

Turning to the large institutions, the total contribution of the BCs to large banks' aggregate lending growth is generally more volatile, compared to the estimates for the small institutions. On the one hand, this is due to the fact that lending growth is more volatile as well, especially on a bank-individual basis. On the other hand, the number of observation in this group is considerably smaller, namely around 360 per quarter, which gives individual banks a relatively larger weight in the group-specific aggregate. Very high values of BCs of a few individual banks can thus end up having an undesirably large effect on the $BC's$ total contribution to aggregate lending. Figure 2.4 depicts the goodness of fit of the aggregation method in equation (2.2).





The left graph depicts the goodness of fit for small banks' aggregate lending over time, whereas the analog for the large institutions is presented in the right graph. *gL agg obs* denotes the observed aggregate lending in the stratified sample as defined in section 2.2.1. The *estimated* series stems from the estimated cross-sectional model (2.2), leaving aside the aggregate error term $\sum_i \omega_{i,t-1}\varepsilon_{i,t}$. The *conservative* series is based on the result using the robust aggregation method, which is described in the Appendix.

Figure 2.4: Goodness of Fit

The difference between the observed series and the estimate is the aggregate error term $\sum_i \omega_{i,t-1}\varepsilon_{i,t}$. The dashed lines represent the conservative estimates, as explained in the Appendix. The conservative estimate only uses observations with observed balance sheet characteristics within a certain range for the aggregation procedure, to avoid a potentially distortionary effect of a few very large BC values. Indeed, this estimate provides a slightly better fit than the full sample estimate for the large banks.

The aggregate goodness of fit for the group of small institutions is already very high with the standard aggregation method ($R^2 = 99.3\%$)[16], which suggests that the careful handling of the data, as described in section 2.2.1, efficiently takes care of extreme outliers and consequently the individual errors are uncorrelated with the share in aggregate lending, and hence with the size of the institutions. The results for the small institutions virtually do not change with the more conservative aggregation method.

As the aggregate fit is not perfect ($R^2 = 85.3\%$) and the exclusion of very high BC values changes the dynamics of estimated aggregate lending of large banks[17], I will henceforth concentrate on the conservative results for this size-group as presented in Table 2.4, which generally decrease the absolute contribution of the balance sheet characteristics to observed aggregate lending[18] and therefore can be seen as a lower absolute bound. The general results however do not depend on whether the plain or the conservative aggregation method is employed.

Another valid critique concerns the feedback effect of individual large banks on the macroeconomic environment, which in turn could affect the estimated lending sensitivities[19]. While this case cannot be disproved, as a 'clean', feedback-free, measure of lending growth is not obtainable, the natural channels through which feedback effects may work do not change the general results here. The adequate robustness checks are performed in section 2.3.2.

$ExtFin$ contributes around 65% to the variation in large banks' aggregate lending growth and is the single characteristic with the highest contribution. Two distinctive points, the spike in Q3 2007 and the spike in Q3 2008, stick out (Figure 2.2). Both are periods of distress and institutions with high ratios of external finance apparently could or had to provide noticeably more funds, compared to institutions with a higher degree of equity and deposit funding. These spikes occur in periods when large institutions were forced to provide backstop liquidity to off-balance sheet vehicles (Brunnermeier (2009)). Part of the effect shows up in UC as the spike in the corresponding lending sensitivity (Figure 2.3), but the

[16] In addition, the estimated contributions to aggregate lending change only marginally with the conservative estimate, which suggests that the sample of small institutions is robust to very high values of the BCs. The corresponding results are reported in the Appendix.

[17] The conservative estimate does not decrease the aggregate goodness of fit at all. The R^2 of 86.8% is even slightly higher than the R^2 obtained from the full sample.

[18] The estimates over the full sample, provided in the Appendix, are quantitatively very similar. Assigning a lower absolute contribution for each of the BCs, can however eliminate the aggregation error which arises, since some individual banks have a non-marginal influence on aggregate lending growth. Therefore the conservative estimates most likely provide a more precise picture of the variance contributions.

[19] Clearly, this problem does not exist among the small banks. The largest bank in the sample has a maximum share of 17.85% in outstanding loans of US bank loans in the sample period, whereas the maximum share of any small institution is less than 0.1% at any point in time.

quantitatively larger part is captured by $Ext\,Fin$. Institutions, which were taking great amounts of assets from their special purpose vehicles back onto their balance sheets, were apparently also institutions with high degrees of external finance. This is consistent with the appearance of the two spikes and it also explains the strong negative effects in the following periods, Q4 2007 and Q4 2008, when exactly those institutions had to freeze their credit supply. The reason why this effect is not picked up by the change in unused commitments (UC contributes at max 1% p.Q.) is that in the sample period, liquidity backstop guarantees to off-balance sheet vehicles were not reported as unused commitments and hence UC can, by construction, only represent the effect of a change in unused commitments tied to actual loans appearing on the balance sheet. In the present setup, the effect is driven by the possibility to raise external finance, or in this incident, the potential downside risk of taking on too much external debt, which has materialized. Note that, since the absolute contribution of $Ext\,Fin$ to aggregate lending is mostly negative in the pre-crisis period, banks with lower external finance ratios supplied more loans. Additional loans must have been financed by new external debt, however, since banking sector levels of $Ext\,Fin$ were rising substantially.

Similar to the small institutions, where the additional loans were supplied by banks with relatively higher equity ratios, more conservatively funded large institutions were also supplying additional loans. The difference i,s however, that the potential for supplying more credit is generated by the availability of external finance and not by relatively larger equity buffers. Again, this trend started to reverse sharply during the crisis, leading to a rapid decline in banking sector external financing ratios, and at the same time to a decline in aggregate lending.

Eq itself also explains a significant part of the pre-crisis lending growth dynamics. Nevertheless, the equity restriction was almost never binding, as the average absolute contribution is slightly negative (-1.2% p.Q.). Large banks were apparently managing their core equity well and, in times when the restriction became more binding, lending growth was reduced which generates a negative variance contribution to aggregate lending growth.

Both sources of funding of last resort, $Fed\,Fund$ and $FHLB$, as expected, contribute negatively to the dynamics of lending growth. Institutions which require more of these types of funding are not able to do so via the interbank or capital markets, which signals distress. The more this is necessary in the aggregate to maintain credit supply, the more severe the stress is in the banking sector, and hence the negative correlation with aggregate lending growth. Consequently, $Fed\,Fund$ and $FHLB$ can explain a notable amount of the variation in aggregate lending.

To some extent this also holds true for the risk proxies. Whereas almost no explanatory power adheres to $Risk\,wt$, both the net interest margin NIM and the share of overdue loan in total loans *Due* bear some relevance to aggregate lending dynamics. The average absolute impact of *Due* is at around -2% p.Q. during the crisis, compared to -1% before. The increased share of over-due loans thus shifts down the average lending growth per quarter by 1 percentage point. This effect does not vary a lot over time and, therefore, the variance contribution is quite small. This is not the case for NIM. Before the crisis, banks with a higher NIM supplied relatively more credit, increasing lending growth in the aggregate. This additional risk taking was reversed after Q3 2008, as banks with a lower net interest margin lended more (absolute negative effect), in cycle with lending growth.

2.3 Macroeconomic Determinants of Aggregate Lending Dynamics

Ultimately, banks will decide upon the project they would like to finance after taking into account the economic environment. At times when the economic outlook is strong and a persistent growth in economic activity is expected, it is optimal to supply more credit, compared to recessions, or times of high uncertainty. Both demand and expected default rates are affected by changes in the economic environment and, hence, the individual-specific balance sheet constraints will be more or less binding as well. It would for example be optimal to hold a higher share of loans to total assets and to have a lower equity ratio during upturns, whereas, in downturns, a higher equity buffer and a relatively lower weight for loans in the asset portfolio is more desirable. In turn, the lending sensitivity with respect to *Eq* should *ceteris paribus* be lower and the β associated with *Risk wt* should *ceteris paribus* be higher under favorable economic conditions compared to periods of economic distress.

The aim of this section is to analyze how far lending sensitivities, and consequently aggregate lending dynamics, are driven by macroeconomic and financial factors. For this purpose, I use four groups of macroeconomic factors, which should comprise the decisive pieces of information on which the banks under consideration were basing their lending decisions before and during the crisis. For each group, the first principal component of the member variables[20] is calculated to serve as the proxy for the corresponding factor. The four macro-factors and the corresponding variables are

[20] The principal components are calculated on the basis of standardized (mean zero and unit variance) variables. *Delinq* is multiplied by -1 in order to get a consistent group, in which variables do not move into opposite directions when hit by the same macro shocks. With *in*creased economic activity, economy wide delinquencies rates are typically *de*creasing.

1. Economic Activity: GDP, I, $Delinq$
2. Interest Rates / Refinancing Costs: $FF\,rate$
3. Expected Economic Conditions: $MIC\,Conf$, ISM, $\Delta BUS\,1y$, $BUS\,5y$
4. Financial Market Risk: $AB\,Spread$, $TED\,Spread$, VIX, $S\&P\,Vol$

for which definitions and details are provided in Table 2.5. The first two macro-factors are widely used in the literature, whereas economy-wide delinquency rates are considered in addition, as they are a potentially relevant factor for banks' assessment of current macroeconomic conditions. Since lending decisions are mostly longer-term commitments, not only current, but also *expected,* economic conditions matter for deriving the optimal credit supply. Here, I use several survey measures, assuming they reflect the common expectation regarding the future state of the economy. Finally, a factor for financial market risk is considered, to mirror refinancing conditions. If the perceived risk and the price of risk on financial markets are low, banks can more easily obtain funding at a low cost from the capital market, which can extend, in particular, large banks' capacity to supply credit.

As shown in the previous section, almost all of the variation in aggregate lending is due to adjustments in the lending sensitivities[21]. Recall that the β's are estimated in an unrestricted way, in the sense that they are allowed to vary freely over time. These two features make apparent the virtue of the Kashyap and Stein (2000) approach. If changes in the economic environment influence lending decisions, then the induced variation in the estimated betas is the channel through which lending is affected in the aggregate. The unrestricted estimation does not preimpose any comovement with the common factors above and it captures the dynamics of aggregate lending very closely. Hence, it allows to analyze *how much* of the variation in lending sensitivities can be explained by comovements with common macro factors and therefore more generally, whether a major part of the credit expansion before the crisis and the credit contraction during the crisis can be attributed to the changes in the macroeconomic environment, or, whether the lending dynamics are not driven by fundamentals at all.

[21] With the exception of *Due* and UC, as shown above. Those two factors are excluded from the time-series analysis (2.4) but are again taken into account for the panel model, as the coefficient estimates on the interaction terms reflect both the variation in lending sensitivities and the BCs.

Macro-Factor	Underlying Variables	Variable Description
Economic Activity ($Macro\,Act$)	GDP, I	Growth in Gross Domestic Product (GDP) and Investment (I). Seasonally adjusted data, from the Federal Reserve Flow of Funds.
	$Delinq$	Delinquency Rates on Loans and Leases on total loans as calculated by the Federal Reserve and published on their website. $Delinq$ enters negatively into the factor $Macro\,Act$. Delinquent loans and leases are those past due thirty days or more and still accruing interest as well as those in non accrual status.
Interest Rates ($Int\,Rates$)	$FF\,rate$	Quarterly average Fed Funds rate in % p.a. as published on the Federal Reserve Board website.
Expected Economic Conditions ($Macro\,Exp$)	$MIC\,Conf$	Consumer Confidence Index from Thomson Reuters/University of Michigan Surveys of Consumers.
	ISM	Purchasing Managers Index from the Institute of Supply Managers. Obtained from Datastream.
	$\Delta BUS\,1y$	Index for expected change in business conditions in a year. From Thomson Reuters/University of Michigan Surveys of Consumers.
	$BUS\,5y$	Index for business conditions expected during the next five years. From Thomson Reuters/University of Michigan Surveys of Consumers.
Financial Market Risk ($Fin\,Risk$)	$AB\,Spread$	Index of spread between Aaa and Baa rated bonds in % p.a.. Data from Federal Reserve website.
	$TED\,Spread$	Spread between the 3-month Libor rate and the 3-month T-bill rate in % p.a.. Libor rate is the quarterly average of the London Interbanking rate for 3-month loans in USD. The Libor rate.is from Wall Street Journal, the 3-month T-Bill rate from the Federal Reserve Board website.
	VIX	Chicago Board Options Exchange Market Volatility Index. Measure of implied volatility of S&P 500 index options. Obtained from Datastream.
	$S\&P\,Vol$	Ex-post volatility of the S&P 500 index. Calculated as the within quarter variance of returns on the S&P 500 index. Obtained from Datastream.

The *Macro-Factor* is the first principal component of the *Underlying Variables* as described above.

Table 2.5: Description of Macro and Financial Market Variables

The structural model for describing the beta dynamics is:

$$\beta_{j,t} = \phi_{j,0} + \phi_{j,1} M_{1,t-1} + \phi_{j,2} M_{2,.t} + \phi_{j,3} M_{3,t-1} + \phi_{j,4} M_{4,.t} + u_{j,t} \tag{2.4}$$

where M_k denotes the k-th macro-factor as defined above. The constant $\phi_{j,0}$ is added, as the first principal components have a zero mean. Banks are assumed to make their credit supply decisions on the basis of the information which is available up to time t. The macro-factors 1 and 3 are lagged by one period[22] to take account for the fact that the information on macroeconomic data and surveys is not available in real time, but is usually published later. The principal components for interest rates and financial market risk are calculated on the basis of quarterly averages of the underlying daily observations. This data is readily available in real time and thus M_2 and M_4 enter as contemporaneous values in regression (2.4). Table 2.6 presents the results. The estimates *var cont beta* provide the variance contribution of the macro factor to the lending sensitivities from equation (2.4), measured in percent. Analogous to the variance contribution of lending sensitivities to aggregate lending in equation (2.3), they are calculated as

$$var\,cont\,beta\,(j,m) = \frac{cov\left(\beta_{j,t},\phi_{j,m}M_{m,t(-1)^*}\right)}{var\left(\beta_{j,t}\right)} \tag{2.5}$$

where $M_{m,t(-1)^*}$stands for $M_{m,t}$ for $m = 1,2$ and $M_{m,t-1}$ for $m = 2,4$.

2.3.1 Small Institutions

Whereas a major part of the variation in those betas, which are most relevant for small banks' aggregate lending, can be explained by the macro and financial factors, the comovement between the large institutions' lending sensitivities and the common factors is not very pronounced. Figure 2.5 visualized how much of the variation in the unrestricted *Eq* beta of small institutions and the unrestricted $Ext\,Fin$ beta of large banks can be explained by the 4 macro-factors together.

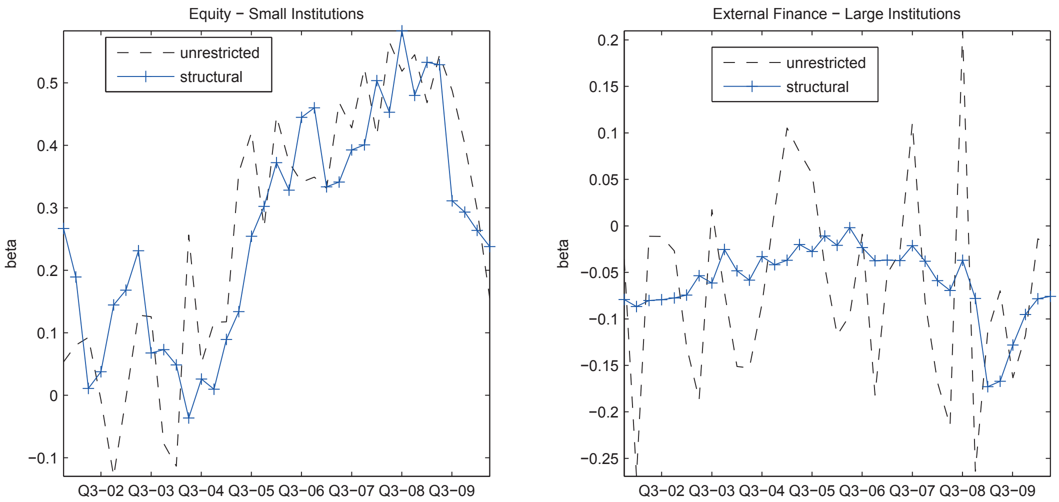
The most significant part of small banks' aggregate lending is obviously driven by changes in expected macroeconomic conditions. This factor is able to explain about half of the variation in the *Eq* lending sensitivity and 50% of the changes in the *Risk wt* beta. In line with previous findings in the literature, equity is more of a restriction, when expectations about future economic conditions are deteriorating. Notably, *expected* economic conditions matter rather than the current state of the economy, as the impact of the $Macro\,Act$ factor is insignificant and small. As Figure 2.6 shows, expected economic conditions were already trending downwards long before the crisis, with a short but strong rebound in the beginning of 2007. Even after the rebound, banks with a stronger core equity ratio were still contributing positively to lending growth and hence taking on additional risks. With the arrival of the crisis, the economic outlook deteriorated sharply, and the equity restriction became crucial until expectations started improving again. Consistent with the risk-taking story from the previous section, *Risk wt* comoves positively with $Macro\,Exp$. As the economic outlook improves, the impact of risk-taking strengthens until Q3 2008, when both trends reverse. Overall, a significant part of

[22]Running the regression on contemporaneous values of M has no notable effect on the results.

							Small Institutions						
			Exc		*Risk*				*Ext*	*Sec*	*Fed*		*NI*
	Const	*Eq*	*Tier2*	*Constr*	*wt*	*NIM*	*Liq*	*Hold*	*Fin*	*act*	*Funds*	*FHLB*	*Inc*
Macro Act	0.120	-0.016	0.008	0.126**	0.005	-0.039	-0.001	0.065*	-	0.004	0.003	0.006***	0.009
var cont beta	-3.507	4.835	9.903	7.094	13.091	-7.766	-2.162	6.246	-	-1.784	1.043	1.721	0.177
Int Rates	-1.624***	0.085***	-0.014	0.604***	0.004	0.121***	0.005***	-0.039	-	-0.023**	0.011	-0.005	0.073
var cont beta	47.943	8.844	0.737	43.154	1.170	27.683	11.938	-1.158	-	10.256	2.269	0.910	0.355
Macro Exp	-0.368	-0.077***	0.016***	-0.230***	0.016***	0.023	0.002	-0.058*	-	-0.005	0.007	-0.005**	0.089
var cont beta	5.277	48.640	30.452	12.237	50.251	3.351	5.570	2.932	-	1.325	2.311	9.362	2.520
Fin Risk	-0.313	-0.002	-0.001	-0.009	0.006	-0.019	0.001	-0.010	-	0.000	0.010***	0.001	0.054
var cont beta	-4.162	-0.604	1.771	0.332	-9.991	6.648	-0.985	0.536	-	0.114	6.968	1.166	-0.379
R2	0.456	0.617	0.429	0.628	0.545	0.299	0.144	0.086	-	0.099	0.126	0.132	0.027
							Largest 5% Institutions						
Macro Act	-0.324	0.010	-0.012	0.407	0.007**	0.054	0.006***	0.032	0.017	-0.001	-0.031**	-0.022	0.087
var cont beta	1.257	-0.290	-1.026	5.236	2.791	2.908	5.816	1.745	8.516	0.010	18.539	7.362	0.835
Int Rates	-1.360**	-0.059	0.008	1.805**	0.021***	-0.085	0.007	-0.181	0.004	-0.029	0.010	-0.003	0.018
var cont beta	3.266	2.035	0.150	16.877	11.019	1.744	5.501	-0.427	0.812	11.724	-1.451	0.485	0.119
Macro Exp	-0.787	-0.025	0.016	-0.114	0.002	0.164	-0.002	0.205***	-0.008	0.011	0.004	0.019	-0.120
var cont beta	2.720	0.828	2.395	-0.297	-0.692	18.837	1.329	15.630	-1.686	7.389	-1.648	0.402	0.841
Fin Risk	-1.226***	-0.019	-0.013	0.099	0.014***	0.099**	0.006***	-0.168***	-0.007	-0.001	0.017	0.007	-0.048
var cont beta	8.677	0.110	2.170	-0.925	13.757	-0.575	7.734	12.691	3.224	0.095	10.629	1.878	0.452
R2	0.159	0.027	0.037	0.209	0.269	0.229	0.204	0.296	0.109	0.192	0.261	0.101	0.022

The Table presents the estimated coefficients ϕ_j of the time-series regression (2.4). The 90%, 95% and 99% confidence levels of the coefficient estimates are indicated by one, two and three * respectively, which are calculated on the basis of heteroskedasticity and auto-correlation corrected Newey-West (1987) standard errors with four lags, to account for seasonality effects. *var cont beta* is the estimated variance contribution of the corresponding macro factor to the time series of estimated unrestricted betas $\beta_{j,t}$ from equation (2.5), measured in percent. $R2$ is the share of explained variance of the $\beta_{j,t}$ by all four macro-factors.

Table 2.6: Macro-Factors and Lending Sensitivities



Plotted are the unrestricted beta estimates $\beta_{j,t}$ from equation (1) and the structural estimates $\sum_m \sum_j \phi_{j,m} M_{m,t-1}$ from equation (2) for the corresponding balance sheet characteristic j. This is to show, how much of the time-variation in the lending sensitivities $\beta_{j,t}$ can be captured by the four macro-factors $M_1 ... M_4$.

Figure 2.5: Explanatory Power of the Macro Factors for the Unrestricted Eq (Small Institutions) and $Ext\,Fin$ (Large Institutions) Lending Sensitivities.

the dynamics in both Eq and $Risk\,wt$ is rationalized by changes in expectations about macroeconomic conditions.

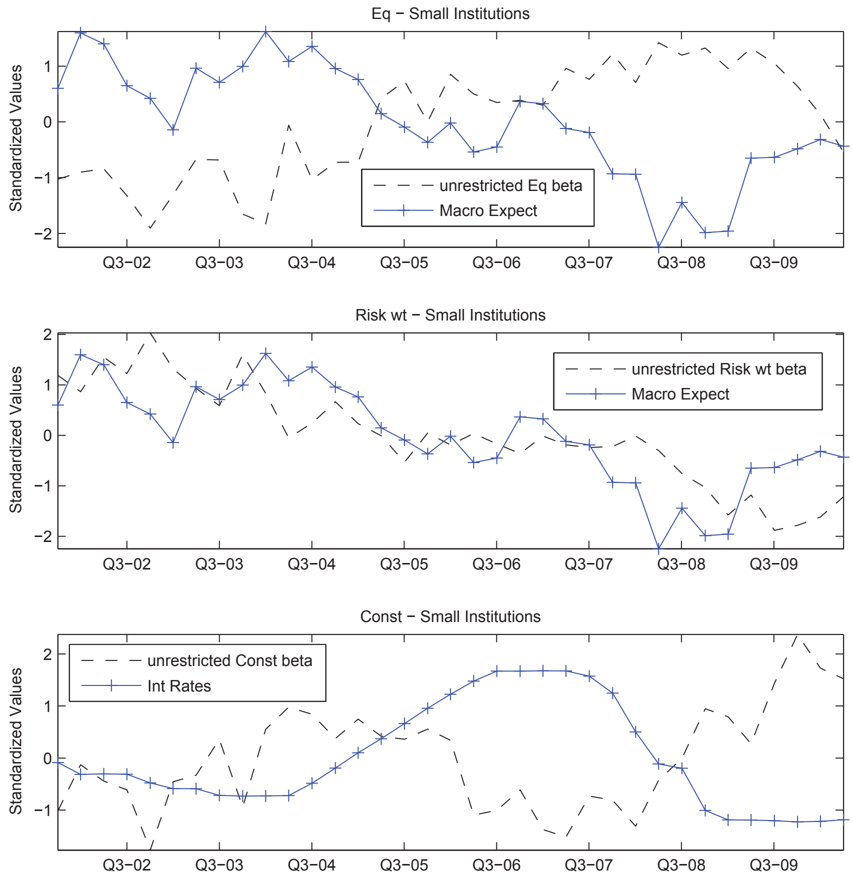
In line with previous findings in the literature (Kashyap and Stein (2000), Kishan and Opiela (2000)), the Liq and Eq restrictions are more binding when interest rates rise; and this effect is smaller for larger banks. However, the quantitatively largest impact of interest rate changes on lending growth dynamics works through the common factor μ, of which's time-variation it explains close to 50%. When interest rates are lowered, the component unrelated to bank-individual characteristics μ increases. If μ is interpreted as excess demand, the implication from this setup is that the quantitatively relevant effect of interest rate changes is rather a demand effect, than a lending channel effect.

With respect to the small institutions, $Fin\,Risk$ and $Macro\,Act$ do not have notable explanatory power for lending sensitivities and consequently for small bank aggregate lending.

2.3.2 Large Institutions and Robustness Issues

Large banks' lending sensitivities, on the other hand, do not seem to be strongly driven by the fundamental factors. $Fin\,Risk$ loads significantly on μ and $Risk\,wt$, but can account only for 8% and 13% of their respective time-variation. A similar picture emerges for interest rates. In particular, the lending sensitivities with respect to $Ext\,Fin$ show no significant relationship with any of the macro and financial factors.

Possible flaws in the time-series estimation could be due to seasonality effects or exceptional exogenously induced spikes in both the betas and the exogenous factors. As a large part of lending is attributed to real estate loans, which are highly seasonal, this effect may have been transferred to the respective betas, which would bias the estimated ϕ coefficients.



The plots show the unrestricted beta estimates $\beta_{j,t}$ from equation (1) versus selected Macro-Factors for the class of small banks.

Figure 2.6: Macro-Factors versus Unrestricted Betas

In addition, some time-particular effects like the Hedge-Fund crisis in Q3 2007 or the collapse of Lehman in Q3 2008 may generate spurious ϕ estimates. As a robustness-check, regression (2.4) is run with appropriately filtered data[23]. As Table 2.9 in the Appendix confirms, the results for either size group hardly change. On average, the explanatory power of the macro and financial market proxies strengthens, however, changes are minor and in no instance qualitatively alter the results.

A second issue, raised in Kashyap and Stein (2000), is the extensive parametrization in the two-step estimation procedure. They suggest a panel data setup, which can be derived by using the parametrization of equation (2.4) for the betas to be estimated in the repeated cross-sectional regression (2.1). This restricted setup now allows the coefficients γ to vary only in accordance with the macro factors M, which are interacted with the bank characteristics BC:

$$\begin{aligned} gL_{i,t} &= k + \sum_m \gamma_m M_{m,t-1} + \sum_j \gamma_{j,0} BC\left(j\right)_{i,t-1} \\ &\quad + \sum_m \sum_j \gamma_{j,m} BC\left(j\right)_{i,t-1} M_{m,t(-1)*} + \varepsilon_{i,t} \end{aligned} \tag{2.6}$$

The panel setup allows the number of parameters for each size group to be reduced to less than one seventh of the parameters in the unrestricted repeated cross-section setup. This comes at the cost of a less flexible model, as less of the time series variation in lending sensitivities can be covered. On the upside, in particular for the group of large banks, which does not provide such an abundant number of observations, the γ estimates from the panel setup yield statistically more precise estimates than the ϕ coefficients from the two step procedure. If a significant part of the variation in lending sensitivities can be reproduced by the four M factors, then the estimates should be quite similar. Table 2.7 summarizes the results of the pooled OLS regression (2.6). Reassuringly, the estimates do not differ decisively. The explanatory power of $Macro\,Exp$ for the Eq and $Risk\,wt$ betas for the group of small banks is slightly lower, but this is picked by the factor capturing current macroeconomic conditions, $Macro\,Act$. Also, interest rates remain the main driver of the constant term μ. Mostly, with the γ estimates from the panel regression, even more of the variation in the original unrestricted betas is replicated, compared to using the ϕ estimates in regression (2.4), which is reflected in the higher corresponding R2s.

The estimates for the large institutions, as expected, deviate slightly more from the values obtained from the two step procedure. Nevertheless, the general results remain unchanged. $Ext\,Fin$ still does not comove significantly with any of

[23] The employed filter is a symmetric band-pass filter, with oscillation of the filtered components between 2 and 4 quarters. A description can be found in Christiano and Fitzgerald (1999).

	Small Institutions														
			Exc		*Risk*					*Ext*	*Sec*	*Fed*		*NI*	
	Const	*Eq*	*Tier2*	*Constr*	*wt*	*NIM*	*Due*	*Liq*	*Hold*	*Fin*	*act*	*Funds*	*FHLB*	*Inc*	*UC*
Macro Act	0.122	-0.022***	0.012**	0.130	0.007***	-0.040**	-0.051***	-0.002**	0.049	-	-0.000	0.002	0.008***	0.040*	0.003
var cont beta	-3.553	6.957	15.205	7.272	16.236	-7.952	38.223	-4.299	4.729	-	0.222	0.754	2.553	0.801	1.863
Int Rates	-1.179***	0.094***	-0.026***	0.573***	-0.002	0.096***	0.036***	0.006***	-0.038	-	-0.013	0.003	-0.010***	0.067*	0.013***
var cont beta	34.793	9.848	1.361	40.941	-0.743	21.929	-7.097	15.305	-1.120	-	5.531	0.521	1.833	0.327	5.321
Macro Exp	-0.173	-0.070***	0.011***	-0.160**	0.011***	0.058***	-0.014*	0.002**	-0.074***	-	0.010	0.004	-0.008***	0.136***	0.007***
var cont beta	2.479	44.043	20.191	8.501	34.412	8.529	7.758	4.833	3.734	-	-2.933	1.246	15.566	3.858	1.835
Fin Risk	-0.138	0.005	-0.006*	0.024	0.003**	-0.007	0.001	0.001	-0.017	-	0.007	0.007*	-0.001	0.106***	0.006**
var cont beta	-1.836	1.438	7.701	-0.856	-4.740	2.664	0.359	-0.643	0.893	-	3.601	4.509	-1.541	-0.745	-3.450
R2	0.483	0.849	0.740	0.616	0.844	0.814	0.976	0.271	0.939	-	0.143	0.207	0.744	0.281	0.978
	Largest 5% Institutions														
Macro Act	0.988	-0.007	-0.005	0.710	-0.014	0.235**	-0.002	-0.005	0.172	0.076***	0.009	-0.087***	-0.073***	-0.386***	0.024
var cont beta	-3.831	0.191	-0.411	9.135	-5.682	12.764	0.095	-5.350	9.298	37.045	-0.121	51.638	24.217	-3.684	-2.934
Int Rates	-0.050	-0.234***	0.092*	0.287	0.023	-0.202	0.155	0.004	0.106	0.061**	-0.055***	-0.058	-0.066**	0.044	-0.011
var cont beta	0.121	8.013	1.792	2.681	11.889	4.133	12.692	3.581	0.250	11.244	22.493	8.400	10.597	0.295	0.863
Macro Exp	0.845	-0.059	-0.015	-0.116	-0.005	-0.041	-0.056	0.004	-0.069	0.046**	-0.022**	-0.066***	-0.031	0.337***	0.031**
var cont beta	-2.920	1.958	-2.239	-0.303	1.879	-4.713	7.910	-3.086	-5.247	10.181	-14.236	28.362	-0.638	-2.357	-3.657
Fin Risk	0.267	-0.127**	0.067*	0.898*	0.003	0.089	0.224**	-0.002	-0.189	0.045**	-0.009	-0.040	-0.041*	-0.014	0.011
var cont beta	-1.890	0.726	-11.529	-8.359	2.793	-0.515	5.572	-2.820	14.295	-21.124	0.933	-25.103	-11.474	0.135	2.349
R2	0.113	0.159	0.135	0.153	0.305	0.135	0.808	-0.044	-0.138	0.511	0.196	0.437	0.496	-0.169	0.862

The Table presents the estimated coefficients of the panel regression (2.6). The 90%, 95% and 99% confidence levels of the coefficient estimates are indicated by one, two and three * respectively. *var cont beta* is the estimated variance contribution of the corresponding macro factor to the time series of estimated unrestricted betas $\beta_{j,t}$ calculated as $cov\left(\beta_{j,t}, \gamma_{j,m} M_{m,t(-1)^*}\right) / var\left(\beta_{j,t}\right)$, measured in percent. $R2$ is the share of explained variance of the $\beta_{j,t}$ by all four macro-factors $\sum_m \sum_j \gamma_{j,m} M_{m,t(-1)^*}$.

Table 2.7: Panel Estimation Results

the M factors. $Macro\,Act$ can explain around 10% of the variation now, but the coefficient estimate is not statistically different from zero, even at a 90% significance level. Interest rates seem to have a slightly higher impact on several lending sensitivities, but in no occasion exhibit a noteworthy explanatory power.

As mentioned above, another possible bias in measuring the comovement of macro and financial factors with the estimated β's could stem from the non-trivial size of some large institutions. During the crisis, a feedback effect from the actions of the biggest lenders in the US to the state of the macroeconomy and the financial markets is likely to have been at work. Whereas this cannot be ruled out, a check whether a crisis feedback effect is strongly influencing the above results for the large banks is feasible. For this purpose, I re-estimate the panel model with observations until Q3 2008 only. If the estimates are similar to the ones for the whole sample, the feedback effect most likely did not alter the results in a pivotal way. At the same time, this approach can reveal sample stability issues, caused by potential structural breaks in the comovement between lending sensitivities and the state of the macroeconomy. One decisive difference for the large banks becomes apparent. $Ext\,Fin$ is now driven to a greater extent by the macro and financial factors. Using the pre-crisis sample and the panel setup, more than half of the variation in the original cross-sectional $Ext\,Fin$ beta in the pre-crisis time span can be replicated with the four M factors. As all the other estimates are very similar, this difference is most likely attributable to a structural break. Indeed, when the panel data model is estimated on the crisis period (Q3 2008 - Q2 2010) only, the loadings on $Int\,Rates$, $Macro\,Exp$ and $Fin\,Risk$ change signs. The γ on the interaction term of $Macro\,Act$ and $Ext\,Fin$ however remains similar, which accounts for the explanatory power of the pre-crisis sample estimates. As noted in the previous section, in both periods the availability of external finance was affecting aggregate lending dynamics of large banks in the same way. As however the values of the M factors clearly change with the crisis, the correlation flipped as well. The structural break can in principle have been caused by feedback effects, but there is no a priori reason why this should have affected exclusively the $Ext\,Fin$ lending sensitivities in a significant way.

The estimates for the small institutions do not seem to suffer from sample stability issues as Table 2.10 in the Appendix confirms. Clearly, the original dynamics of the constant term cannot be mirrored, but this is well-expected, since in the panel setup the unrestricted time-fixed effects, which capture a lot of the variation in aggregate lending, are substituted by the plain M factors, which naturally cannot absorb an equally high amount of the common effect. Nonetheless, the main results pointed out above persist. Even though the additional variation caused by the crisis can be expected to emphasize the comovement of lending sensitivities with the state of the macroeconomy, the estimates from the pre-crisis sample can still replicate the major part of the time-series dynamics of the full-sample unrestricted betas.

2.4 Conclusions

The central point of this paper is the question of what drives US aggregate bank lending in the period between Q1 2001 and Q2 2010.

Individual banks' lending decisions are made on the basis of their balance sheet characteristics, taking into account current and expected economic conditions. How sensitive lending decisions are with respect to banks' balance sheet characteristics (BCs) in the cross section, at a given point in time, therefore signals how relevant the respective balance sheet characteristic is for aggregate lending. With a consistent aggregation procedure, I derive a taxonomy of bank balance sheet characteristics, meaning a classification of the importance of a wide variety of BCs for the time-variation in aggregate lending.

Small banks' aggregate lending is mainly driven by three characteristics: core equity (Eq), the riskiness of its business model measured by the Basel I risk weight ($Risk\,wt$) and a common component μ, which can be interpreted as a excess demand effect. A solid core equity ratio proved crucial for strong lending growth, both before and during the crisis. The high impact of relatively riskier small banks on lending growth before Q3 2008 suggests a certain momentum in risk taking. Both effects can however, to a significant extent, be explained by improving expectations regarding future macroeconomic conditions. Interest rates have statistically significant loadings on the lending sensitivities with respect to equity and liquidity ratios, as documented in the lending channel literature. The quantitatively largest effect, however, works through the common component. A 1 percentage point lower interest rate shift small banks' aggregate lending growth upward by more than 1.5 percentage points. The interest rate effects through Eq and Liq, on the other hand, are negligible.

Large institutions' aggregate lending also shows a significant dependence on core equity. The characteristic with the highest measured impact, however, is the external financing ratio ($Ext\,Fin$), which also proxies how well an institution can obtain funding from the capital markets. Similar to the small institutions, where the additional loans were supplied by banks with relatively higher equity ratios, more conservatively funded large institutions were also supplying additional loans. The difference is, that the capacity for supplying more credit is generated by the availability of external finance and not by relatively larger equity buffers. With the outbreak of the crisis, this effect reversed, together with a general decline in external financing ratios. Generally, the lending decisions of large banks do not seem to be driven by changes in macroeconomic factors, such as current macroeconomic activity, interest rates, expectations of future economic conditions, or financial market risk. This result may be spurious due to possible feedback effects from the actions of large financial institutions to the macroeconomy and financial markets. A more robust estimate, using only observations until Q2 2008, suggests that 50% of the pre-crisis impact of $ExtFin$ on large banks' aggregate lending could be explained by the four macro-factors, in particular by macroeconomic activity.

Overall, the findings of this paper suggest that a notable part of the strong lending dynamics prior to Q3 2008 was propagated by previously more conservative institutions, which were willing to take on more risks. This additional risk-taking can, to a significant extent, be rationalized by a favorable economic environment. Furthermore, the very limited bindingness of liquidity constraints on the asset side, for both large and small banks, suggests, that the extraordinary actions by the Federal Reserve to ensure a sufficient supply of liquidity have been effective.

All of the results above lend themselves to expedient implications for financial regulation. With bullish expectations about future economic conditions, small banks take on additional risks, especially institutions with high equity buffers and already relatively more risky business models. In this light, the recently proposed Basel III regulations, which have a stronger focus on core equity as a capital restriction and also envisage counter-cyclical capital buffers, seem capable to smooth lending dynamics over the business cycle and limit the momentum in risk-taking of small banks.

As for the large banks, a stabilizing effect could be achieved by curbing excessive funding through capital markets, especially in strong economic conditions. The degree of capital market financing seems at least a sensible characteristic to monitor by financial regulators, in order to detect a potentially destabilizing reliance on liquidity provision from capital markets.

As this paper confines itself to the analysis of bank lending, the impact of potential substitution effects from other forms of finance is not captured. In particular, against the background of the general tendency of large firms to raise funding from capital markets, the substitution effect for large institutions could be sizable and a more comprehensive analysis would be beneficial in this respect. A similar critique concerns the so called 'shadow-banking' sector. If a sizable share of lending activity is moved to bank-like organizations, banks may react accordingly and be ready to take on more risks to defend their businesses. Equivalently, increased competition in the lending sector in general may have induced a more aggressive risk-taking behavior (Dell'Ariccia et al. (2008)). An interesting extension of the analysis would therefore be to quantify the impact of increased competition on risk-taking, and ultimately aggregate lending, in conjunction with fundamental macroeconomic factors.

Another issue for further research is related to the risk management behavior of a bank. Some of the results here are consistent with a simple risk target story as in Adrian and Shin (2010). If a bank has a value-at-risk target, for example, improving conditions will decreased the perceived risks and free capacities for additional risks and thus lending. With bank-individual data on value-at-risk and other pivotal risk management statistics, this effect could be quantified.

Appendix

Data

The underlying quarterly data from the US call reports is obtained from the FDIC website[24]. The analysis in this paper confines itself to the time period of Q1 2001 to Q2 2010. It comprises FDIC insured institutions in the US, which includes commercial banks, savings banks and savings institutions, and subsidiaries of foreign institutions, which are registered with the FDIC. It does not, however, cover Branches and Agencies of Foreign Bank Offices (FBO's), which are significant suppliers of credit in the US. In the last decade they were responsible for up to 8,6% of total bank lending and up to 21.1% of C&I loans of all commercial banks in the last decade. At the peak in 2007, they held 15.6% of total assets. Foreign branches and agencies are mostly not FDIC insured, so they are not included in the dataset here. In particular, for the analysis of small business loans this poses a problem, as the actual lending figures might differ significantly when FBO's are included. Foreign banks' branches and agencies do file a so called FFIEC 002 form[25], which however does not cover most of the items analyzed here. For the analysis in this Chapter, a restriction to only FDIC insured institutions is unavoidable, given the data limitations. Still, it also seems sensible from a logical standpoint, given the very limited autonomy, and therefore autonomy in bank lending decisions, for foreign branches and agencies.

Banks which are engaged in mergers or acquisitions are removed at the quarter in which the merger takes effect, and also the previous quarter. To avoid a double counting effect, all institutions which are directly owned by another institution in the sample are dropped. In quarters when institutions enter or leave the sample, they are also excluded. Further, US subsidiaries in foreign US affiliated states are not considered. Starting with roughly 282,000 observations, this decimates the dataset by 7,600 observations. Excluding all banks with total assets of less than 25 million USD, as those cannot be regarded as viable credit-supplying financial institutions (Berger and Bouwmann (2009)), cuts the sample by a further 22,400 data points. Some institutions in the sample are acting rather as mutual funds for

[24] http://www2.fdic.gov/sdi/index.asp

[25] See http://www.ffiec.gov/forms002.htm for all the series covered.

Treasury Bills than credit providing institutions and exhibit lending ratios below 10%, liquidity ratios of beyond 90% and risk-adjusted capital ratios of 100% and more. Naturally these observations cannot provide significant information towards cross-sectional determinants of bank lending. Consequently, this group, entailing roughly 19,400 additional observations, is dropped from the sample as well. To prevent that any extreme lending growth decisions, which are most likely driven by other bank specific exogenous circumstances, affect the estimates, observations with above 50% and below -50% net lending growth per quarter[26], as well as observations exhibiting above 100% and below -50% total asset growth in one quarter are wiped out, which reduces the dataset by another 1,000 observations. Securitization activities have to be reported only by banks with total assets greater than $200m. For non-reporting banks, the value of securitized loans is simply set to zero, which most probably comes very close the real value, but in any case will not alter the results in a measurable way. As a last step, extreme outliers and implausible data points are removed. Implausible observations are constituted by institutions with negative equity, negative total assets, negative risk weighted assets, negative risk weights or risk weights larger than 100%, negative net interest margins, negative Fed Funds and FHLB values, and institutions with higher core equity than total risk weighted ($Tier2$) capital ratios. Outliers are defined as observations which are more than 4 standard deviations away from their mean at a given quarter, and this is applied to both net lending growth and all right hand side balance sheet factors in the analysis. At the end, this leaves close to 266,000 observations in the sample, which is equivalent to an average of about 7,400 observation per quarter. The number of institutions at a given quarter is however steadily declining over time. In Q1 2001 there are about 7,900 usable observation, which reduces to slightly above 7,000 in Q2 2010.

Conservative Aggregation Method

The conservative aggregation method works methodically as described in equation (2.2). To avoid a potentially distortionary effect from extreme BC values, some observations are not considered for the aggregation and the weights ω_i are recalculated based on the reduced sample. In particular, the following values are deemed extreme and are therefore excluded from the aggregation:

$Eq > 25\%$	$ExcTier2 > 30\%$	$Risk\,wt > 95\%$	$NIM > 5\%$	$Due > 4\%$
$Liq > 50\%$	$Liq > 50\%$	$Ext\,Fin > 33\%$	$Sec\,Act > 10\%$	$Fed\,Funds > 10\%$
$FHLB > 10\%$	$NI\,Inc < -10\%$	$NI\,Inc > 10\%$	$UC < -10\%$	$UC > 10\%$

[26] See Table (2.1) on how net lending growth is measured exactly.

Approximated Variance Contributions

The variance contributions of the two components $\beta_{j,t}$ and $\sum_i \omega_{i,t-1} BC(j)_{i,t-1}$ to the total impact on aggregate lending of factor j, which according to equation (2.2) is $\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1}$, is approximated as below. A first-order Taylor approximation around the time series mean of the total impact on aggregate lending yields

$$\begin{aligned}
\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1} \approx\; & \overline{\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1}} \\
& + \overline{\beta_{j,t}} \left(\sum_i \omega_{i,t-1} BC(j)_{i,t-1} - \overline{\sum_{i(s)} \omega_{i,t-1} BC(j)_{i,t-1}} \right) \\
& + \overline{\sum_{i(s)} \omega_{i,t-1} BC(j)_{i,t-1}} \left(\beta_{j,t} - \overline{\beta_{j,t}} \right)
\end{aligned}$$

where the upper bar denotes the time series mean.

Then, the variance of $\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1}$ can be decomposed as

$$\begin{aligned}
var\left(\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1} \right) =\; & cov\left(\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1}, \beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1} \right) \\
\approx\; & cov\left(\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1}, \overline{\beta_{j,t}} \sum_i \omega_{i,t-1} BC(j)_{i,t-1} \right) \\
& + cov\left(\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1}, \overline{\sum_i \omega_{i,t-1} BC(j)_{i,t-1}} \beta_{j,t} \right)
\end{aligned}$$

The variance shares for factor j and beta j are defined as

$$\begin{aligned}
var\, share\, beta(j) &\equiv \frac{cov\left(\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i(s),t-1}, \overline{\beta_{j,t}} \sum_i \omega_{i,t-1} BC(j)_{i,t-1} \right)}{var\left(\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1} \right)} \\
var\, share\, factor(j) &\equiv \frac{cov\left(\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1}, \overline{\sum_i \omega_{i,t-1} BC(j)_{i,t-1}} \beta_{j,t} \right)}{var\left(\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1} \right)}
\end{aligned}$$

such that

$$var\, share\, beta(j) + var\, share\, factor(j) \approx 1$$

where the approximate equality stems from the first-order approximation above.

For all estimated total impacts the first order approximation is sufficiently precise and yields an R2 higher than 0.99.

	gL agg	*Const*	*Eq*	*Exc Tier2*	*Constr*	*Risk wt*	*NIM*	*Due*	*Liq*	*Hold*	*Sec act*	*Fed Funds*	*FHLB*	*NI Inc*	*UC*
							Pre-Crisis - Small Institutions								
mean (% p.Q.)	2.6	0.448	2.6	-0.464	-0.001	4.4	-2.6	-0.914	-0.027	-0.603	-0.002	-0.013	-0.091	0.093	-0.009
min (% p.Q.)	1.3	-3.3	-0.244	-1.1	-0.049	1.1	-4.5	-1.4	-0.633	-1.2	-0.012	-0.107	-0.306	-0.364	-0.232
max (% p.Q.)	4.2	4.2	6.2	0.16	0.041	9.2	-0.748	-0.621	0.646	-0.259	0.015	0.091	0.093	0.476	0.344
var share beta			0.979	1	0.996	1	1	0.479	1	1	0.946	1	1	0.98	0.01
var share BC			0.021	-0.023	0.004	-0.04	-0.004	0.521	-0.001	-0.028	0.054	-0.009	-0.035	0.02	0.99
corr beta - BC			0.694	0.563	-0.386	-0.716	0.132	0.147	0.209	0.514	-0.1	0.333	0.437	-0.28	0.38
agg g_ L var cont	100	168	58.2	-9	0.041	-139	3	4.4	-4.1	12.4	-0.071	-1.5	-0.963	3.1	4.4
							Crisis - Small Institutions								
mean (% p.Q.)	0.479	0.747	4.4	-0.769	-0.02	0.364	-1.7	-1.7	0.031	-0.7	-0.001	-0.068	-0.121	0.069	0.181
min (% p.Q.)	-0.954	-1	1.7	-1	-0.048	-0.769	-2.4	-2.1	-0.477	-0.839	-0.002	-0.166	-0.264	-0.182	-0.037
max (% p.Q.)	2.2	2.4	5.6	-0.109	0.015	1.9	-0.52	-1.1	0.383	-0.429	0.001	0.039	0.1	0.406	0.39
var share beta			1	1.1	0.988	0.949	0.972	0.091	1	1	0.794	1	1.1	1.1	0.019
var share BC			-0.003	-0.051	0.012	0.051	0.028	0.909	0	0	0.206	-0.04	-0.108	-0.055	0.981
corr beta - BC			-0.191	0.846	-0.564	0.494	-0.361	0.308	-0.027	0.038	-0.483	0.897	0.802	-0.516	0.641
agg g_ L var cont	100	-81.3	78.4	-10.4	2	69.6	-7.9	9.2	12.6	7.8	-0.04	5.2	3.7	2.6	10.4

Summarized are the results of the repeated cross-section estimation (2.2), however, including a full set of state dummies instead of one constant. *Const* is simply the sum over all estimated state-constants $\sum_s \beta_{s,t} \sum_i \omega_{i,t-1} d(s)_{i,t-1}$, where s denotes the states. The dummy $d(s)_{i,t-1}$ is equal to one, if institution i is registered in state s, and zero otherwise. The results pertain to the class of small banks as defined in section 2.2.1. *mean* is the time-series mean of $\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1}$, and *min* and *max* are the corresponding minimum and maximum values. *var share beta* and *var share BC* are the first-order approximations of the variance contribution of $\beta_{j,t}$ and $\sum_i \omega_{i,t-1} BC(j)_{i,t-1}$ respectively, to the total effect $\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1}$. Details concerning the approximation are provided in the Appendix. The time-series correlation between the estimated coefficients $\beta_{j,t}$ and the banking sector levels $\sum_i \omega_{i,t-1} BC(j)_{i,t-1}$ is given by $corr\, beta - BC$. $var\, cont\, agg\, gL$ is the variance contribution of $\beta_{j,t} \sum_i \omega_{i,t-1} BC(j)_{i,t-1}$ to aggregate lending $gL_{agg,t}$, as explicated in equation (2.3) expressed in percent. The column $gL\, agg$ provides the respective statistics for within size-group aggregate lending growth.

Table 2.8: The Taxonomy of Bank Balance Sheet Characteristics - Small Institutions - State Dummies

	Small Institutions												
			Exc		*Risk*				*Ext*	*Sec*	*Fed*		*NI*
	Const	*Eq*	*Tier2*	*Constr*	*wt*	*NIM*	*Liq*	*Hold*	*Fin*	*act*	*Funds*	*FHLB*	*Inc*
Macro Act	0.148	-0.005	0.002	0.201***	0.005	-0.053***	-0.001	0.080*	-	0.015**	0.001	0.007***	-0.001
var cont beta	-4.655	1.563	3.118	13.571	12.105	-11.335	-3.056	7.333	-	-5.773	0.523	3.518	-0.024
Int Rates	-1.770***	0.062**	-0.006	0.573***	0.007	0.140***	0.005***	-0.042	-	-0.033***	0.014	-0.006*	0.019
var cont beta	54.895	6.489	0.370	41.597	2.399	34.022	14.600	-1.361	-	14.232	3.047	1.306	0.106
Macro Exp	-0.569***	-0.108***	0.027***	-0.227***	0.021***	0.040**	0.002***	-0.073*	-	-0.016***	0.011*	-0.005**	0.106
var cont beta	10.549	70.809	56.462	8.927	70.414	7.869	4.706	4.598	-	9.050	4.847	9.494	3.668
Fin Risk	-0.476***	-0.020	0.004	0.040	0.011***	-0.013	0.001*	-0.008	-	-0.001	0.012**	0.001	0.051
var cont beta	-6.710	-6.359	-5.240	-1.270	-17.756	4.326	-1.703	0.413	-	-0.683	6.404	1.478	-0.604
R2	0.611	0.789	0.707	0.804	0.678	0.521	0.353	0.141	-	0.319	0.199	0.268	0.034
	Largest 5% Institutions												
Macro Act	-0.227	0.003	-0.032	0.241	0.005	0.120	-0.066	0.007**	-0.055	0.019	0.005	-0.030**	-0.022
var cont beta	0.708	-0.114	-1.538	3.064	1.403	7.960	3.142	6.902	-2.608	9.262	0.361	17.075	7.289
Int Rates	-1.455*	-0.038	0.009	2.238***	0.021**	-0.134	0.233***	0.006	-0.081	0.017	-0.035***	-0.007	-0.017
var cont beta	3.885	1.515	0.187	20.657	11.560	2.185	18.878	5.566	-0.117	2.817	13.947	0.881	2.519
Macro Exp	-0.720	-0.004	0.012	0.443	0.001	0.113	-0.044	-0.002	0.279***	0.010	0.006	-0.017	0.000
var cont beta	1.020	0.013	1.568	2.248	-0.386	10.767	5.808	2.051	21.606	3.201	3.137	8.433	-0.010
Fin Risk	-1.106**	-0.004	-0.030*	0.583*	0.011**	0.102	-0.014	0.007***	-0.170*	0.014	-0.003	-0.006	-0.015
var cont beta	4.677	-0.069	5.843	-3.858	7.159	-2.393	-0.333	8.358	12.655	-3.503	0.465	-2.869	-1.108
R2	0.211	0.027	0.152	0.434	0.334	0.270	0.365	0.367	0.531	0.224	0.344	0.428	0.167

The Table presents the estimated coefficients of the time-series regression (2.4), based on the band-pass filtered macro-factors and lending sensitivity estimate. The employed filter is a symmetric band-pass filter, with oscillation of the filtered components between 2 and 4 quarters. A description can be found in Christiano and Fitzgerald (1999). The 90%, 95% and 99% confidence levels of the coefficient estimates are indicated by one, two and three * respectively, which are calculated on the basis of heteroskedasticity and auto-correlation corrected Newey-West (1987) standard errors with four lags, to account for seasonality effects. *var cont beta* is the estimated variance contribution of the corresponding macro factor to the time series of estimated betas $\beta_{j,t}$, as given in equation (2.5), measured in percent. $R2$ is the share of explained variance of the $\beta_{j,t}$ by all four macro-factors.

Table 2.9: Macro-Factors and Lending Sensitivities - Band-Pass Filtered Data

								Small Institutions							
	Const	*Eq*	*Exc Tier2*	*Constr*	*Risk wt*	*NIM*	*Due*	*Liq*	*Hold*	*Ext Fin*	*Sec act*	*Fed Funds*	*FHLB*	*NI Inc*	*UC*
Macro Act	0.596**	-0.017	0.011	0.039	-0.003	-0.007	-0.039**	-0.002*	0.087*	-	-0.003	-0.015*	0.006*	0.050	0.011**
var cont beta	-17.349	5.347	14.504	2.178	-6.140	-1.446	29.856	-5.399	8.389	-	1.634	-5.535	1.903	0.993	6.736
Int Rates	-0.548*	0.085***	-0.013	0.342*	-0.019***	0.186***	0.023	0.006***	0.030	-	-0.024	-0.012	-0.012**	0.279***	0.028***
var cont beta	16.177	8.902	0.701	24.466	-5.758	42.499	-4.403	16.439	0.891	-	10.462	-2.503	2.142	1.355	11.454
Macro Exp	0.093	-0.081***	0.021***	-0.265**	0.006**	0.066***	0.002	0.002**	-0.018	-	-0.003	-0.005	-0.008***	0.270***	0.015***
var cont beta	-1.334	50.889	40.789	14.084	17.969	9.672	-1.400	6.844	0.893	-	0.858	-1.666	15.839	7.645	3.784
Fin Risk	-0.343	-0.014	0.002	-0.197	0.007**	-0.014	0.034**	0.003**	0.002	-	0.015	0.006	-0.008**	0.187***	0.008*
var cont beta	-4.560	-4.409	-3.026	7.022	-10.354	5.038	21.825	-2.511	-0.089	-	8.047	3.866	-10.550	-1.310	-4.834
R2	0.684	0.790	0.611	0.635	0.948	0.755	0.983	0.435	0.937	-	0.220	0.308	0.789	0.437	0.981
								Largest 5% Institutions							
Macro Act	0.988	-0.007	-0.005	0.710	-0.014	0.235**	-0.002	-0.005	0.172	0.076***	0.009	-0.087***	-0.073***	-0.386***	0.024
var cont beta	-3.831	0.191	-0.411	9.135	-5.682	12.764	0.095	-5.350	9.298	37.045	-0.121	51.638	24.217	-3.684	-2.934
Int Rates	-0.050	-0.234***	0.092*	0.287	0.023	-0.202	0.155	0.004	0.106	0.061**	-0.055***	-0.058	-0.066**	0.044	-0.011
var cont beta	0.121	8.013	1.792	2.681	11.889	4.133	12.692	3.581	0.250	11.244	22.493	8.400	10.597	0.295	0.863
Macro Exp	0.845	-0.059	-0.015	-0.116	-0.005	-0.041	-0.056	0.004	-0.069	0.046**	-0.022**	-0.066***	-0.031	0.337***	0.031**
var cont beta	-2.920	1.958	-2.239	-0.303	1.879	-4.713	7.910	-3.086	-5.247	10.181	-14.236	28.362	-0.638	-2.357	-3.657
Fin Risk	0.267	-0.127**	0.067*	0.898*	0.003	0.089	0.224**	-0.002	-0.189	0.045**	-0.009	-0.040	-0.041*	-0.014	0.011
var cont beta	-1.890	0.726	-11.529	-8.359	2.793	-0.515	5.572	-2.820	14.295	-21.124	0.933	-25.103	-11.474	0.135	2.349
R2	0.113	0.159	0.135	0.153	0.305	0.135	0.808	-0.044	-0.138	0.511	0.196	0.437	0.496	-0.169	0.862

The Table presents the estimated coefficients of the panel regression (2.6) *for the pre-crisis period*, Q1 2001 - Q2 2008, only. The 90%, 95% and 99% confidence levels of the coefficient estimates are indicated by one, two and three * respectively. *var cont beta* is the estimated variance contribution of the corresponding macro factor to the *full* (Q1 2001 - Q2 2010) time series of estimated unrestricted betas $\beta_{j,t}$ calculated as $cov\left(\beta_{j,t}, \gamma_{j,m} M_{m,t(-1)^*}\right) / var\left(\beta_{j,t}\right)$, measured in percent. *R2* is the share of explained variance of the $\beta_{j,t}$ by all four macro-factors $\sum_m \sum_j \gamma_{j,m} M_{m,t(-1)^*}$ for the *pre-crisis period*.

Table 2.10: Panel Estimation Results - Pre-crisis Period (Q1 2001 - Q2 2008)

Chapter 3

The Real Effects of Liquidity and Financial Market Conditions A Threshold VAR Approach

3.1 Introduction

Adverse conditions on the financial market are considered to be one of the main propagators of the financial crisis in 2007-2009[1] and real effects of financial market conditions are documented widely in the literature. A seminal paper is Bernanke (1983), who argues that adverse financial market conditions lead to higher costs of credit intermediation. More recently, a number of papers have focused on liquidity effects and pro-cyclical behavior of financial intermediaries. Brunnermeier and Pedersen (2009) highlight the link between market liquidity, the ease at which assets are traded, and funding liquidity, the ease at which the necessary funding can be obtained. In their model, funding and market liquidity mutually reinforce each other, leading to downward spirals when bad shocks occur. As a result, liquidity has an effect on asset price volatility. Adrian and Shin (2010) argue that banks' balance sheets provide information about funding liquidity. In a marking to market environment, US investment banks managed their balance sheets according to Value-at-Risk (VaR), increasing leverage when the VaR goes down. A growth in leverage indicates increased funding liquidity in the financial sector, as the demand for assets increases. They confirm the implications of Brunnermeier and Pedersen (2009), as they find that leverage growth can predict future market volatility. He and Krishnamurty (2008) develop a model where intermediary capital affects the risk bearing capacity of the marginal investor.

As a common feature and testable implication arises that both liquidity effects

[1]see Brunnermeier (2009) for a summary on the financial crises

and changes in uncertainty should have an effect on economic activity; either directly, or indirectly through the capacity and willingness to supply credit to the real economy. Furthermore, the feature that liquidity effects are potentially self-enforcing and pro-cyclical suggests a transmission mechanism which differs depending on whether favorable or adverse shocks occur, and whether those shocks are large enough to induce the self-enforcing feedback spirals or not.

The aim of this paper is to quantify the real effects of liquidity spirals, financial market risk and credit supply, taking into account the fundamentally different behavior of "good" versus "bad"[2] cycles.

The idea, that there are different regimes and agents behave fundamentally different in "good" conditions compared to "bad" conditions, is also a common feature across many credit market models, as for example in Blinder (1987) or Azariadis and Smith (1998). Further, the propagation of shocks can differ hugely, like in von Hagen and Zhang (2008). Empirically, the identification of different regimes and non-linearities in shock transmissions have been studied in conjunction with monetary policy by Sims and Zha (2006), and many others, on the basis of Markov Switching Models, in which transition probabilities, and thus regime switches, are not endogenously determined however.

This paper adopts a regime switching Threshold VAR, to capture the feature of distinctively different transmission mechanisms. One virtue of the TVAR model is that it allows the regime to be selected endogenously, depending on the other variables and shocks in the system. It creates both non-linear and conditional dynamics in response to structural shocks[3]. Therefore, the TVAR model is general enough not only to capture different transmission mechanisms *conditional* on endogenous variables like financial market conditions, but also to generate different responses depending on the size and direction of structural shocks.

A prominent application of a univariate type of this model is Potter (1995), who studies regime dependent shock transmissions to US GNP. Artis et al. (2007) take the TVAR approach to study non-linear transmission of shocks between countries. Shen and Chiang (1999) use a TVAR model in the same style as the one employed here to study non-linear monetary policy shock transmissions depending on the economy being in a low or a high inflation regime. The paper closest to the one in hand is Balke (2000), where credit conditions determine the regime of the economy, which is characterized by output, inflation, interest rates, and the threshold variable determining the credit regime.

This paper incorporates proxies for funding liquidity, credit supply conditions, interest rates, uncertainty, and overall financial market conditions in the TVAR,

[2] Ben Bernanke in his Feb 24th testimony before the Senate Banking Committee used the term "adverse feedback loop"

[3] See for example Shen and Chiang (1999) for an application on the Monetary Transmission Mechanism

using US data from Q1 1990 to Q1 2009. Overall financial market conditions, approximated by the TED spread, serve as an endogenous threshold and determine the prevailing regime. I will shed light on the joint empirical dynamics of these variables in the 2-regime TVAR and illustrate how financial market conditions change the transmission mechanisms in the macroeconomy, which are shown to be distinctively different in the two regimes.

The next section provides an overview over the Econometric Model and explains and justifies the inclusion of the variables under consideration. Section 3 presents the results, and section 4 concludes.

3.2 Econometric Model and Endogenous Variables

A simple and versatile method to model the behavior of a set of variables with two distinctly different dynamics, where the regime is determined endogenously, is a 2 Regime Threshold VAR with an endogenous threshold. The Threshold VAR is a multivariate generalization of the Self-Exciting Threshold Autoregression (SETAR) model proposed by Tong (2005), and a simpler version of the Threshold cointegration VAR introduced by Lo and Zivot (2001). It can be expressed in reduced form as

$$Y_t = I\left(q_t \leq \gamma\right)\left[A_1\left(L\right)Y_t + \varepsilon_t^1\right] + I\left(q_t > \gamma\right)\left[A_2\left(L\right)Y_t + \varepsilon_t^2\right] \tag{3.1}$$

where q_t is the threshold, which is also an element of the vector of endogenous variables Y_t. Y_t is comprised of GDP growth, credit supply, leverage growth, the change in the Fed Funds rate, the change in the VIX index, and the TED spread.

$$Y_t = \left[\begin{array}{cccccc} g_{GDP} & g_{CredSup} & g_{lev} & \Delta FFrate & \Delta VIX & TED \end{array}\right]' \tag{3.2}$$

The used data is for the US, from Q1 1990 to Q1 2009, in quarterly frequency. The threshold element in Y_t is defined as $Y_t^q = q_t$, and q_t is the TED spread. $I\left(q_t \leq \gamma\right)$ is the indicator function, which generates the regime shift. It is equal to I, the identity matrix, if $q_t \leq \gamma$ (regime 1), or 0 otherwise (regime 2). In the time periods when q_t is above the threshold, the dynamics of Y_t are governed by the autoregressive process $A_2\left(L\right)Y_t+\varepsilon_t^2$, and if $q_t \leq \gamma$, then $Y_t = A_1\left(L\right)Y_t+\varepsilon_t^1$. Hence, if γ is known, the model reduces to an OLS estimation on two distinct samples, for which the sample split is identified by whether q_t is above or below the threshold γ. In the setup here however, γ is required to be determined endogenously, and therefore is not known in advance. This makes the model non-differentiable with respect to γ. To estimate the jointly optimal parameters, a simple complete search for $\hat{\gamma}$ over of all unique elements[4] in q_t is performed. Given a value for γ,

[4]The actual grid search is performed only over the $1-\pi$ percent of all unique element, and the smallest and largest values for q_t are not considered as a valid optimal threshold $\hat{\gamma}$, since too

the estimates for the lag polynomials $A_1(L)$and $A_2(L)$ (which always include a constant) can be consistently estimated by simple OLS[5]. The γ candidate which generates the minimal log determinant of the sum of squared errors

$$\min_{\gamma} log\left(\left|\begin{pmatrix} \varepsilon_t^1 \\ \varepsilon_t^2 \end{pmatrix}'\begin{pmatrix} \varepsilon_t^1 \\ \varepsilon_t^2 \end{pmatrix}\right|\right)$$

is then the threshold estimate $\hat{\gamma}$. To take account for different sizes of shocks in each regime, the covariance matrix of errors is allowed to differ across regimes:

$$\begin{cases} E\left[\varepsilon_t^1\left(\varepsilon_t^1\right)'\right] = \Omega_1 & \forall t : I\left(q_t \leq \gamma\right) \\ E\left[\varepsilon_t^2\left(\varepsilon_t^2\right)'\right] = \Omega_2 & \forall t : I\left(q_t > \gamma\right) \end{cases}$$

A test for the existence of a threshold γ is conducted according to Hansen (2002)[6].

3.2.1 Endogenous Variables

The Threshold VAR system comprises proxies for economic growth, credit supply conditions, funding liquidity, changes in volatility, changes in interest rates, and financial market conditions, which serve as the threshold. The aim is to measure the effects of funding liquidity, financial market risk, and credit supply on economic growth. In addition, I am interested in the mutual effects among the variables in the system, allowing for different transmission mechanisms depending on the regime of the economy.

Funding liquidity is proxied by commercial bank leverage growth, calculated from the Federal Reserve's Flow of Funds Commercial Bank data as Total Assets divided by the difference of Total Assets and Total Liabilities, from quarterly seasonally unadjusted data. As has been argued by Adrian and Shin (2010), investment banks increase their leverage in response to an increase in the value of their existing asset portfolio, which creates a strong pro-cyclical effect of banks' demand for assets and hence their supply of funding. The focus in this paper,

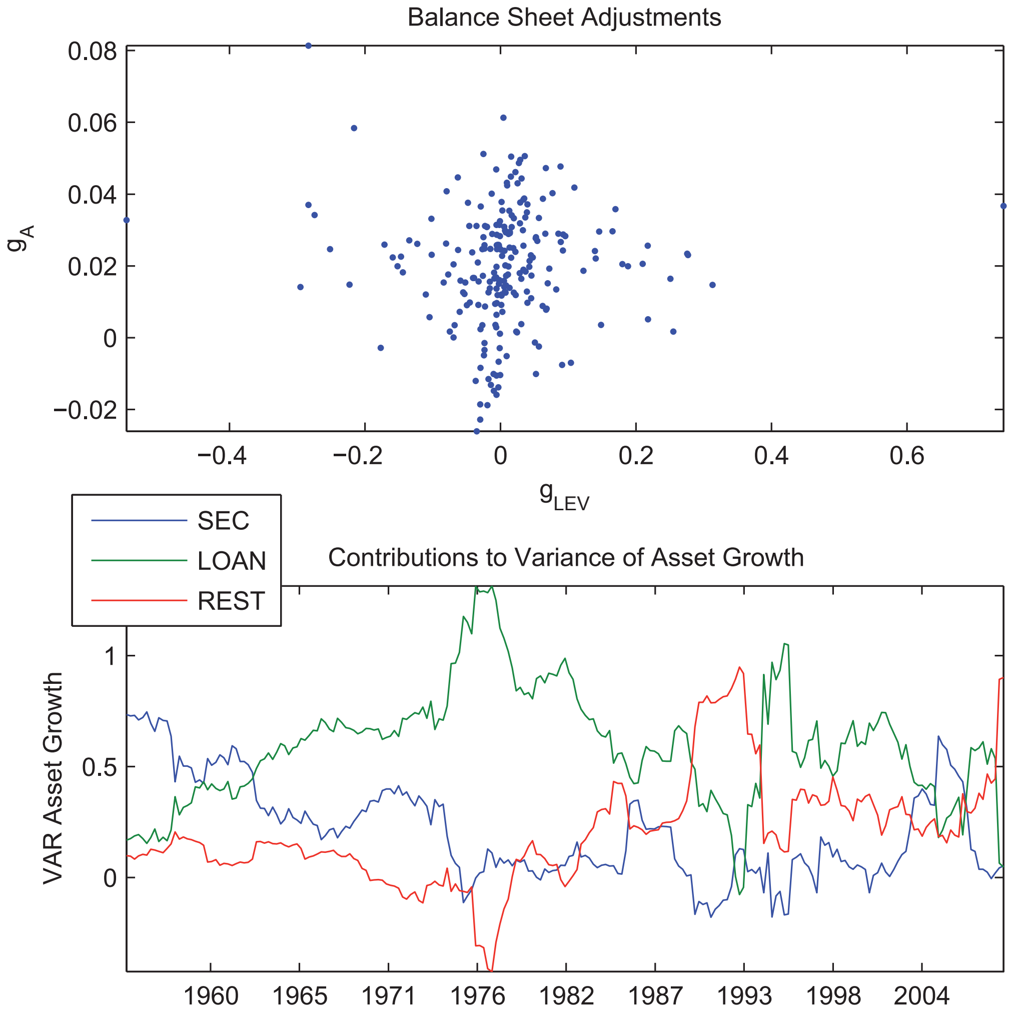
few observations would remain to estimate the coefficients $A(L)$ for one of the regimes. In order to maximize the statistical power, π should be between 5 and 15% (see Tong (2005)). The results here are checked against sensitivity in π, but any value between 5 and 15% leads to exactly the same threshold value.

[5]The same applies for restrictions imposed on the parameter matrices $A_1(L)$and $A_2(L)$. For example certain variables can be allowed to enter in regime 2 only, or parameters can be restricted to be equal in both regimes.

[6]Hansen (2002) is a multivariate generalization to Hansen (1996). The test here is a special case of a know cointegration vector, as Y_t is assumed to be stationary. Note that the simulated (by fixed regressor bootstrap) test statistic is based on a heteroskedasticity consistent covariance estimator. Therefore, the structure proposed here fits entirely into the testing setup; including possible restrictions on the parameter matrices.

however, is rather on commercial banks, as they are one of the most important provider of funds to the real economy. The upper panel of Figure 3.1 shows that commercial banks target a certain leverage ratio, which is likely to be determined by the regulatory framework. When the value of commercial banks' assets increase, this would *de*crease their leverage ratio, if banks were acting passively. On the contrary, evidence for active balance sheet management can be observed. To maintain the target leverage ratio, banks further increase their asset holdings in response to an increase in the value of assets. Adrian and Shin's basic argument is thus also valid for commercial banks. In a prosperous environment, in which the value of assets increases, banks are trying to expand their asset portfolio. This is a pertinent point, as it implies that an exogenous increase in asset values spurs a further increase in demand for assets. To illustrate which types of assets are affected, the lower panel of figure 3.1 shows the covariance contribution of securities, loans, and other assets to the variance of asset growth. In the run-up to the 2007/2008 crisis, banks were expanding their balance sheets by buying securities, mostly Fannie Mae and Freddie Mac securitized papers. The contribution of loans is positive throughout the whole period, which means that increases in the growth rate of total assets will have a positive effect on the provision of loans. The pro-cyclical expansion of balance sheets will thus increase the supply of funding, or the 'funding liquidity', in the economy. This increase materializes in the form of funding for securities, traditional bank loans, and other assets. When funding liquidity is high, banks will also be able to securitize more loans and resell them for acceptable prices and, as a results, will have spare capacities to provide additional funding (see Altunbas et al. (2009)).

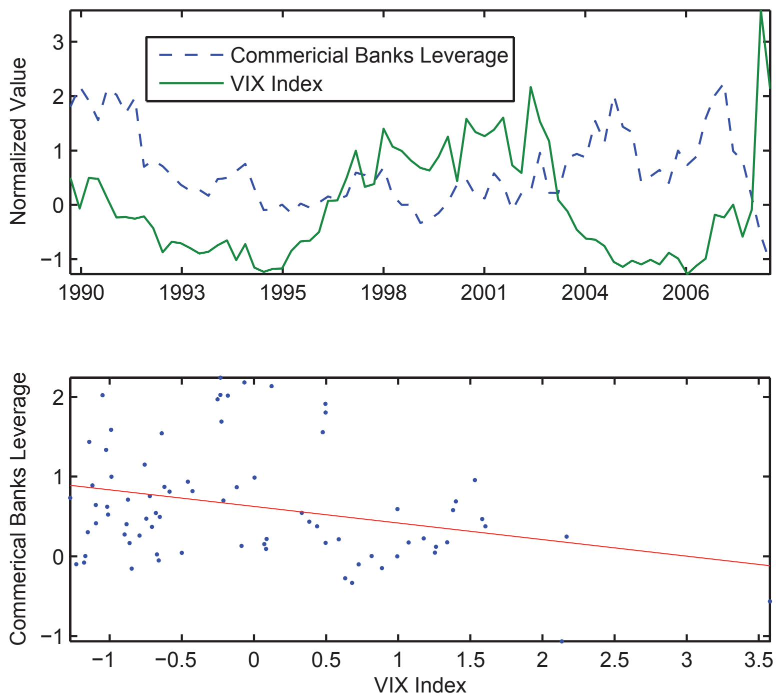
Funding liquidity of banks, and therefore their leverage growth, is linked to the degree of *uncertainty* in financial markets, as argued by Adrian and Shin (2010). When uncertainty rises, the value-at-risk (VaR) increases. The VaR measures the maximum absolute amount of losses which materialize with a given probability. At any time, banks want to maintain a sufficient amount of equity to be able to absorb the possible losses without compromising their solvency. A rise in uncertainty, which automatically increases the VaR, consequently would require banks to hold more equity. As equity is difficult to raise in the short-run, banks reduce the absolute amount of possible losses instead, by selling risky assets. This puts downward pressure on asset prices, and in turn, tightens the capital base even further, as banks have to incur losses on their existing asset portfolios. In a favorable scenario, the analog reverse feedback effects are at work.



Both graphs are based on the data from the Flow of Funds Table 109. The covariance contributions are calculated as follows: Total Assets A_t consist of Loans, Securities and the rest of the asset side balance sheet positions. Thus $A_t = SEC_t + LOAN_t + REST_t$. As an expression of the growth-rate of A this becomes $g_{A_t} = \frac{\Delta SEC_t}{A_{t-1}} + \frac{\Delta LOAN_t}{A_{t-1}} + \frac{\Delta REST_t}{A_{t-1}}$. The relative variance contribution of each constituent is given by $\frac{var(g_{A_t})}{var(g_{A_t})} = \frac{cov(g_{A_t}, g_{A_t})}{var(g_{A_t})} = \frac{cov(\frac{\Delta SEC_t}{A_{t-1}}, g_{A_t})}{var(g_{A_t})} + \frac{cov(\frac{\Delta LOAN_t}{A_{t-1}}, g_{A_t})}{var(g_{A_t})} + \frac{cov(\frac{\Delta REST_t}{A_{t-1}}, g_{A_t})}{var(g_{A_t})}$

Figure 3.1: Leverage Growth versus Asset Growth for Commercial Banks & Margins of Adjustment in Asset Growth

Changes in uncertainty are approximated by the change in the VIX index[7], obtained from Datastream as daily data. It is then transformed into quarterly averages to smooth out high frequency spikes. On this basis, the annualized quarterly growth rate is calculated. Figure 3.2 shows the graphs for leverage growth and the VIX index. Even though leverage is likely to be influenced to a high degree by the regulatory framework, there is a significant negative relationship between expected volatility and the leverage of commercial banks.



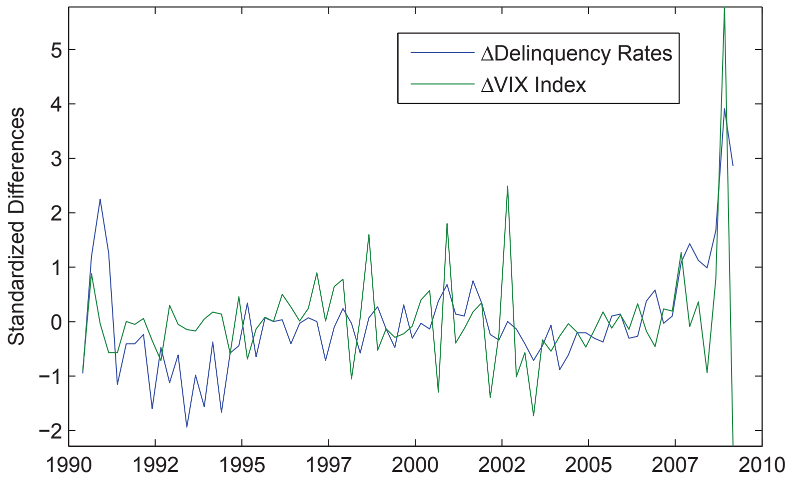
The upper figure plots the normalized (zero mean and unit variance) values of the variables over time. Commercial Banks Leverage is calculated as the aggregate total assets divided over the aggregate equity from the Flow of Funds data obtained from the Federal Reserve website. The lower figure displays the Commercial Banks Leverage versus the VIX index (both normalized) and the least square errors linear fit.

Figure 3.2: Commercial Bank Leverage and Financial Market Volatility

Moreover, expected uncertainty by itself is a propagator of credit supply and economic activity. Lower expected volatility implies lower credit risks for banks

[7]The VIX index captures the implied volatility derived from the prices of the most traded options. Most specifically, the VIX is the square-root of the risk neutral expectation of the S&P 500 variance over the next 30 calendar days and is quoted as an annualized standard deviation in percentage terms. Therefore it is a suitable measure for expected volatility.

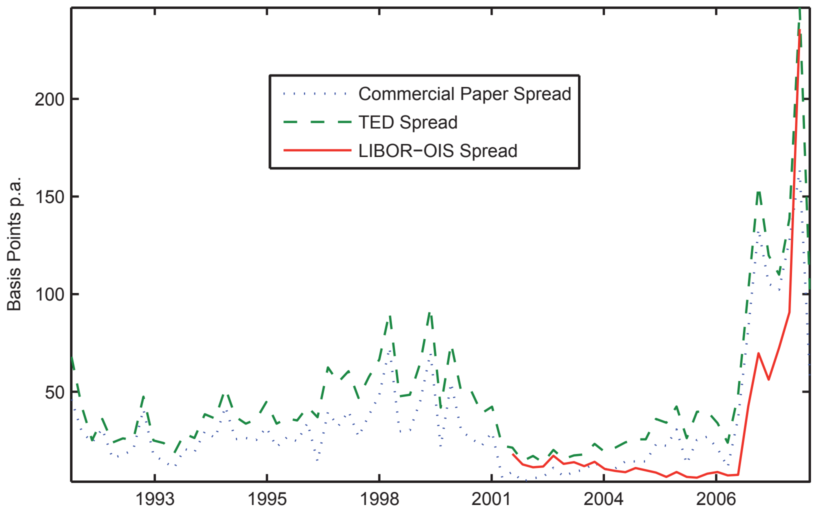
and lower costs of funding for firms, which will increase the overall credit supply and demand and lead to additional economic activity. Figure 3.3 displays the change in seasonally unadjusted delinquency rates on Loans and Leases for Commercial Banks, obtained from the Federal Reserve, for all types of bank loans, together with the change in the VIX index. Statistically, expected volatility clearly contains relevant information about future delinquencies at commercial banks and hence the risks banks are facing, which, in turn, influence their credit supply decisions.



Standardized Differences denote the quarterly changes of the zero mean and unit variance series of delinquency rates and the VIX index. Delinquency rates are for Loans and Leases of Commercial Banks obtained from the Federal Reserve website.

Figure 3.3: Delinquency Rates on Loans and Leases for Commercial Banks and the VIX Index

To distinguish the fundamentally different behavior of "good" and "bad" cycles, the endogenous threshold should capture *financial market conditions* in general. The estimation procedure of the TVAR will select the optimal value of the threshold, as described above. One variable that has been used widely as a suitable indicator of distress in financial and credit markets is the TED spread, which is the difference between the LIBOR (London Interbank Offered Rate) and the rate for 3-month US Treasury Bills. It captures the risk premia for obtaining liquidity in the interbanking market as a markup over T-Bills, which are assumed to carry a very low risk of default. The T-Bill rates also contain a 'flight-to-quality' effect. In rough financial conditions, investors tend to shift their portfolios towards safer assets, in particular the 3-month T-Bill. This technically lowers the yield on T-Bills and blows up the TED spread. If the TED spread is high, it signals distressed conditions, either because of a fear of default in the interbanking market or a substantial flight-to-quality. Both scenarios describe situations when financial markets are under severe stress. The TED spread can hence be considered as a reasonable proxy for financial market conditions in general. In particular, it directly signals, whether banks have funding problems, which is crucial for identifying possible liquidity spirals. Another widely proposed measure in this respect is the LIBOR-OIS spread[8], which is the spread between the average London Interbank Offered Rate and the Overnight Interest Swap for a maturity of 3 months. The OIS is surveyed by Bloomberg, but it is, unfortunately, only available from the end of 2001. Due to this substantial restriction, I will instead be content with the Ted spread. Figure 3.4 plots the quarterly average of the TED spread versus the quarterly average of the LIBOR-OIS spread from Q1 1988 to Q4 2008.



The data on commercial paper spreads is a composite series with the average dealer offering rate for 30 days Commercial Paper for AA rated firms minus the 3 month T-Bill rate until Q4 1996 and from Q1 1997 until Q1 2009 it is the equivalent rate for financial firms only. The LIBOR-OIS spread is the spread between the average London Interbank Offered Rate and the Overnight Interest Swap with a maturity of 3 months from Bloomberg. The data for the other two series is obtained from the Federal Reserve website.

Figure 3.4: LIBOR-OIS, TED and Commercial Paper Spreads

The LIBOR[9] and OIS data is taken from the British Bankers Association website and Bloomberg, whereas the other data is from the Federal Reserve website.

[8]See for example Thornton (2009)

[9]The LIBOR data used here is the 3-month rate for credit agreements denominated in US$.

Qualitatively, the dynamics are quite similar. The TED spread tends to be more volatile, as expected, but moves together with the LIBOR-OIS spread quite well. Additionally, the Commercial Paper spread series is shown to be highly correlated with the TED spread. The Commercial Paper spread is a composite series with the average dealer offering rate for 30 days Commercial Paper for AA rated firms minus the 3 month T-Bill rate until Q4 1996. Thereafter, it is the equivalent rate for financial firms only[10]. The Commercial Paper spread measures the premium which investors demand in order to hold short term debt of highly rated creditors, with very low default risks. As the risk premium for default risks contained in this spread is likely to be very low, the Commercial Paper spread arguably reflects the ease at which refinancing through capital markets; in other words the demand for short-term debt. Its high correlation with the TED spread corroborates the view that the TED spread is an adequate measure of overall financial and credit market conditions.

Credit supply conditions are approximated following Adrian and Shin (2010): The survey data from the Chief Loan Officer is used as an instrument for the total quarterly growth in non-financial debt[11] to isolate the part of total credit, which is correlated with changes in supply conditions. I employ the survey data on commercial and industrial (C&I) loans as well as C&I real-estate loans[12] for both large/medium and small firms, and increased spreads of loan rates over banks' cost of funds. The estimated values from the first stage linear regression constitute the proxy for credit supply conditions. The calculated proxy is plotted in Figure 3.5. It displays nicely an increased supply for the run-up towards the recent financial crisis in 2007/2008, followed by a corresponding sharp decline. The decline at the beginning of the sample can be attributed to the savings and loan crisis.

The interest rate variable in the TVAR is the change in the Fed Funds rate. Both the change in the Fed Funds rate and the TED spread are measured in basis points per annum.

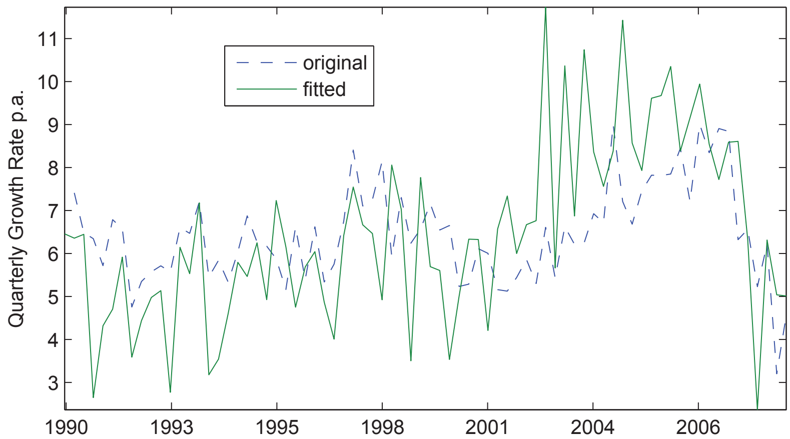
Economic growth is captured by the seasonally adjusted GDP growth rate[13] from the Flow of Funds data of the Federal Reserve.

[10]From 1997 the Fed only reports the Commercial Paper rates for financials and non-financials separately.

[11]Flow of Funds Table 2.

[12]Increased Spreads are not surveyed for C&I real estate loans.

[13]Throughout the paper, growth rates are expressed as the annualized quarterly rate.



The original series is the annualized quarterly growth rate of non-financial credit from the Flow of Funds Table 2. The fitted series is the credit supply proxy, which are the fitted values from a linear regression of the original series on the Chief Loan Officer survey data on commercial and industrial loans on both large/medium and small firms, and increased spreads of loan rates over banks' cost of funds and real estate C&I loans.

Figure 3.5: Credit Supply Proxy

3.2.2 Impulse Response Functions

The impact of a shock in period t on the vector of dependent variables Y_{t+k} in this setup can most easily be defined as[14]:

$$IRF_{t+k|t-1}(v_t) = E\left[Y_{t+k}\left|Y_{t-1}, v_t\right.\right] - E\left[Y_{t+k}\left|Y_{t-1}\right.\right] \tag{3.3}$$

As the regime is allowed to switch endogenously, shocks will generate different impulse responses depending on whether a regime shift occurs. If the economy is in a "good" credit regime, a relatively large positive shock of type j, denoted as $v_{j,t+1}$, might cause an initial regime-switch to the bad regime, given the threshold variable q_t, in response to the shock, exceeds the threshold value γ. A negative shock, on the contrary, would not have had this kind of initial effect. As the dynamics in the "good" and in the "bad" regime are different, the response to a

[14]Note that this formulation is not identical to Koop et al.'s (1996) formulation of non-linear Impulse Response Functions, which is common in this type of literature. The "Generalized" Impulse Response Function is $IRF_{t+k|t-1}(v_t) = E\left[Y_{t+k}\left|Y_{t-1}, v_t, u_{t+1}, ..., u_{t+k}\right.\right] - E\left[Y_{t+k}\left|Y_{t-1}, u_{t+1}, ..., u_{t+k}\right.\right]$, where the $u_t's$ are a series of shocks which hit both expectation terms. Firstly, this simulation exercise consumes a lot of computing time while it changes the results only in a few cases, and if, only to a negligible extent. Secondly, the interpretation of the Impulse Responses proposed here is more straight-forward in the additive non-linear TVAR framework under consideration.

shock v depends on its magnitude and direction. Further, the distance to threshold $\|q_t - \gamma\|$, which indicates how large a positive or negative shock on q_t causes a regime switch, is time-varying. Therefore, depending on the conditioning period t, a shock in $t+1$ of the same size can either cause a regime switch or not, as the distance to threshold in period t can be smaller or greater.

Therefore, the IRFs are, as a result of the regime-switching nature of the model, non-linear functions of both the size of the shock and the conditioning period t; as opposed to a linear VAR system, where the IRFs are homogeneous functions of degree 1 of the size of v and homogeneous functions of degree 0 of the conditioning period t. Naturally, this makes calculating the IRFs relatively more complex.[15] The additional complexity allows, however, to generate completely different dynamics, given the state of the economy and the severity of a shock. The model, for example, would be able to generate dynamics such that an adverse shock on credit market conditions affects economic growth much more persistently, if the shock occurs at a time when the economy is already in a "bad" regime. Or, interest rate shocks could have a much lower initial effect on credit demand in a "bad" regime than in a "good" regime.

While a linear model does not have this kind of desirable features, the TVAR with an endogenous threshold variable does allow for conditional dynamics, whilst being estimable with a simple combination of grid-search and OLS methods.

For illustrative purposes, I will also refer to the linear Impulse Response Function. The linear Impulse Response Function in this setup simply takes the two regimes separately and therefore does not allow for a regime-shift. It is calculated through the normal recursion in exactly the same way as for a linear VAR, using the coefficient estimates and covariance matrix of shocks for the respective regimes. Hence, the linear Impulse Response Functions provide the impacts of a shock, assuming that the economy is permanently in a given regime.

3.2.3 Identification of Structural Shocks

The analysis here focuses on a simple contemporaneous identification scheme. As there is no definite theoretical justification for a restriction on the transmission mechanism or on long term mutual effects, imposing identifying restrictions of any kind would seem overly restrictive in this context. In turn, the issue of interest is, whether the data will let the econometric model indeed detect different regimes and significantly different transmission mechanisms.

As the results are not supposed to be affected a priori by a different identification across regimes, it is natural to apply the same identification scheme for regimes 1 and 2. Note that the transmission mechanism of shocks will neverthe-

[15] A detailed description of how the IRFs are calculated is provided in the Appendix.

less differ across regimes (see the Appendix for details). Also, by assumption, the structural shocks in regime 1 and 2 are uncorrelated.

Given the nature of the variables under consideration, there is, to a certain extent, a natural ordering according to the timing of adjustment. A shock to growth will certainly have a contemporaneous effect on all the other variables, whereas a shock to credit supply conditions will have a contemporaneous effect on the financial market variables, but only a subsequent effect on growth. I further argue, that the bank's balance sheets adjust faster than credit supply conditions, but slower than the remaining financial market variables. As banks balance sheets are comprised of both longer-term (such as private and industrial loans) and shorter-term (traded financial assets and liabilities) items, a shock to leverage growth would affect the financial markets immediately, however would probably take some time to spill into credit supply conditions and GDP growth. As for the group of financial market variables, the ordering is a priori flexible. The ordering underlying the results in the next section is the change in the Fed Funds rate, the change in the VIX index and the TED spread.

The results for other meaningful identification schemes are presented in section 3.3.1.

3.3 Results

Figure 3.6 displays the TED spread and the threshold estimate selected by the model.

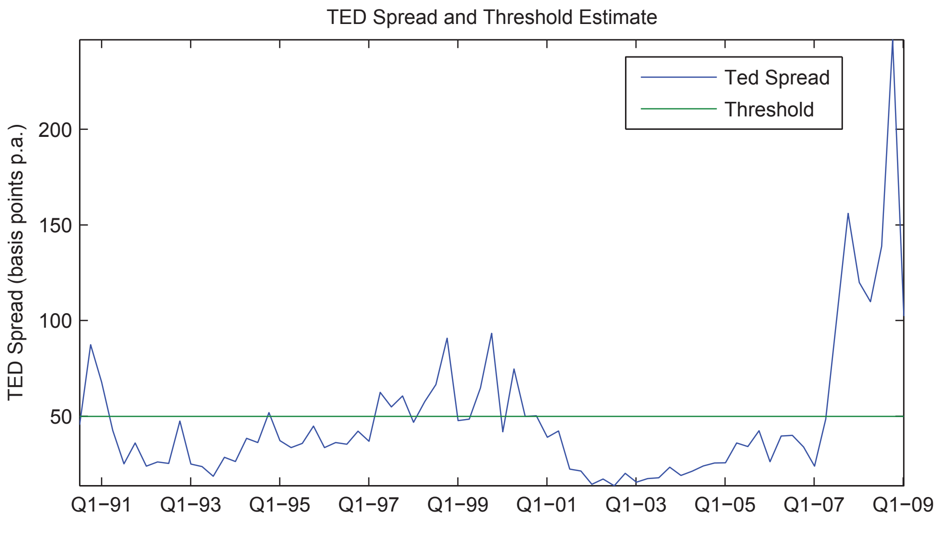


Figure 3.6: The TED Spread and the Threshold Estimate

The division between the "good" regime, which is below and on the threshold, and the "bad" regime is clear-cut and the threshold estimate is at a TED spread of around 50 basis points. The extreme values of the financial crisis fall into the "bad" regime (Q3 2007 until Q1 2009) as well as some periods in the middle of the sample, which include the inflation and the burst of the 'tech-bubble' in Q3 1999/ Q1 2000. Table 3.1 displays the descriptive statistics of the variables in each of the regimes.

	GDP Growth	*Credit Supply Growth*	*Leverage Growth*	*Change FF Rate*	*Change VIX*	*TED Spread*
			Regime 1			
mean	5.11	6.51	0.19	-0.19	-4.97	31.389
std	1.67	1.06	49.4	14.96	56.68	10.19
sum	275.8	351.4	10.5	-10	-268.4	
			Regime 2			
mean	3.91	6.33	-12.09	-7.1	54.2	90.9
std	3.62	1.28	58.78	17.8	151.2	46.57
sum	82.0	132.9	-253.9	-149	1138.1	

Table 3.1: Descriptive Statistics for each Regime

Clearly, the variances are higher in the second regime, as well as the mean values of the change in the VIX index and the TED spread, which both signal distress in financial markets. The parameter estimates of the model are presented in Table 3.2, together with the asymptotic t-stats and the p-value of the Hansen (2002) test for existence of a threshold in this class of models. A p-value of around 4 % is a clear rejection of the no-threshold hypothesis, given the dimensionality of the model. Particularly, as the threshold is a variable of very low persistence, which allows to identify the regimes more precisely, the joint dynamics of the more slowly moving variables in the system may not differ too much across regimes, even though the model detects a sharp regime shift. The Hansen-test, however, strongly supports the view of the two detected regimes exhibiting very different joint dynamics. The optimal lag-length according to the AIC and BIC information criteria are a 1-quarter and 2-quarter lag for the normal regime and a 1-quarter lag for the "bad" regime[16]. The inclusion of only a 1-quarter lag for the "bad" regime is due to the fact that in the "bad" regime, the endogenous variables behave much

[16] The inclusion of higher-order lags up to 4 quarters for regime 1 does not qualitatively change the Impulse Response Functions and results in only marginally different threshold estimates. The only noticeable difference is the impact of a GDP growth shock on GDP itself in regime 1, which is more persistent. In general, the estimates are much less precise such that the results are statistically not different from the more parsimonious setup with 2 lags.

more radically and their joint relationships are obviously not as stable as in the tranquil regime.

	Const	*GDP Growth*	*Credit Supply Growth*	*Leverage Growth*	*Change FF Rate*	*Change VIX*	*TED Spread*
				Regime 1			
GDP Growth	2.31 (1.00)	0.30 (1.53)	0.34 (1.03)	-0.008 (-0.96)	-0.002 (-0.12)	-0.005 (-0.72)	-0.03 (-1.64)
Credit Supply Growth	1.10 (1.10)	0.05 (0.58)	0.82 (5.80)	0.0018 (0.51)	0.0045 (0.55)	0.001 (0.34)	-0.0046 (-0.65)
Leverage Growth	-77.55 (-1.44)	1.15 (0.25)	13.58 (1.78)	-0.35 (-1.81)	-0.15 (-0.34)	0.065 (0.42)	-0.46 (-1.20)
Change FF Rate	-35.36 (-1.13)	2.56 (0.95)	3.6441 (0.82)	0.06 (0.49)	0.29 (1.14)	0.00064 (0.0067)	-0.037 (-0.17)
Change VIX	-13.88 (-0.12)	2.56 (0.26)	0.13 (0.0083)	-0.35 (-0.87)	0.19 (0.20)	-0.13 (-0.40)	-0.25 (-0.31)
TED Spread	3.45 (0.18)	1.24 (0.74)	1.45 (0.52)	-0.040 (-0.56)	0.12 (0.75)	0.059 (1.02)	0.36 (2.59)
				Regime 2			
GDP Growth	8.44 (3.05)	0.23 (0.70)	-0.21 (-0.49)	0.0074 (0.67)	-0.008 (-0.25)	0.0002 (0.03)	-0.046 (-2.81)
Credit Supply Growth	4.44 (3.70)	0.16 (1.12)	0.36 (1.92)	0.0083 (1.73)	-0.029 (-2.10)	-0.005 (-1.79)	-0.014 (-1.92)
Leverage Growth	21.81 (0.34)	-9.62 (-1.26)	16.32 (1.63)	-0.14 (-0.55)	-0.086 (5)	0.069 (0.46)	-1.31 (-3.41)
Change FF Rate	54.41 (1.46)	1.10 (0.25)	-0.0047 (-0.0008)	0.28 (1.84)	-0.99 (-2.31)	-0.11 (-1.30)	-1.10 (-4.78)
Change VIX	-34.35 (-0.25)	1.76 (0.11)	-1.15 (-0.055)	-0.10 (-0.18)	1.62 (1.05)	-0.057 (-0.18)	1.54 (1.91)
TED Spread	-62.04 (-2.64)	1.71 (0.61)	8.65 (2.37)	-0.25 (-2.62)	1.05 (3.89)	0.11 (2.02)	1.23 (8.80)
			Threshold Estimate (TED Spread): 49.9 basis points				
			P-Value of Hansen Test Against Alternative of No Threshold: 0.0420				

Asymptotic t-statistic are given in brackets. Reported estimates are for a model with 2 lags for Regime 1 and 1 lag for Regime 2. For regime 1, the coefficient estimates and t-stats denote the sum of the respective coefficients and joint t-stats over all lags. The p-value of the Hansen (2002) test is calculated with 1000 bootstrap replications. The trimming factor is set to 10% (5% on both ends). Significance at a 1% level is indicated by ***, at 5% by ** and 10% by *.

Table 3.2: Parameter Estimates and Asymptotic Significance

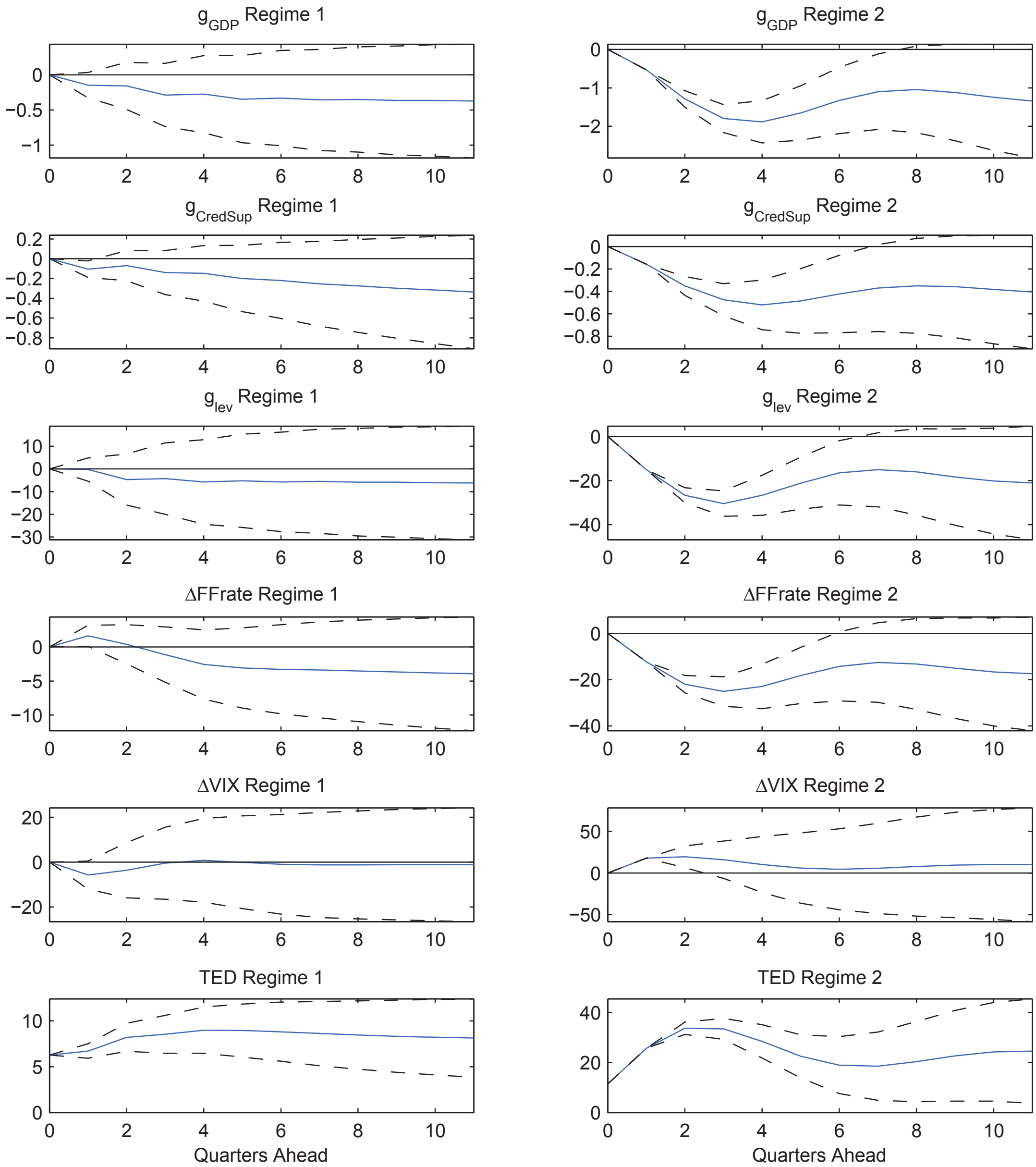
Especially in the financial crisis at the end of the sample, reactions of GDP growth, the TED spread, and leverage growth have barely any relation to their joint levels 6 months ago. Within the “bad” regime it therefore seems natural that only information of the very recent past can have an influence on the current state of the economy.

Generally, the relationships between the endogenous variables are more pronounced and also more likely to be statistically significant in regime 2. In particular, overall financial market conditions, proxied by the TED spread, show a distinctively different impact, depending on the prevailing regime. The linear Impulse Responses[17] of the different variables as a response to a one standard-deviation (1-std) shock in the TED spread are plotted in Figure 3.7. Firstly, financial market conditions exhibit a sizable direct impact on GDP growth. A positive 1-std TED shock, which signals a deterioration in financial market conditions, has a cumulative long-run effect of -1.5 percentage points on GDP growth. Further, the TED shock strongly impacts credit supply growth as well as leverage growth, which is the proxy for liquidity. The cumulative effect on leverage growth is around -20% in the long run. For the 2007-2009 crisis, where extreme quarter-to-quarter changes in the TED spread are observable, this implies a huge pressure for de-leveraging. In the short run, a positive 1-std TED shock has a strong initial impact of +20% on volatility growth as well.

This constitutes first evidence for an adverse feedback loop between liquidity and financial market conditions during times of financial market instability, which is corroborated by the negative and significant estimates of the second regime parameters of the TED spread in the equation for leverage growth, and vice versa. The absence of this self-enforcing effect in the ’good’ regime is an indication for the altering transmission mechanism of liquidity and financial market conditions during financial crisis, as suggested by Brunnermeier and Pedersen (2009) and Frank et al. (2008). However, the real effect of a leverage shock is fairly small.

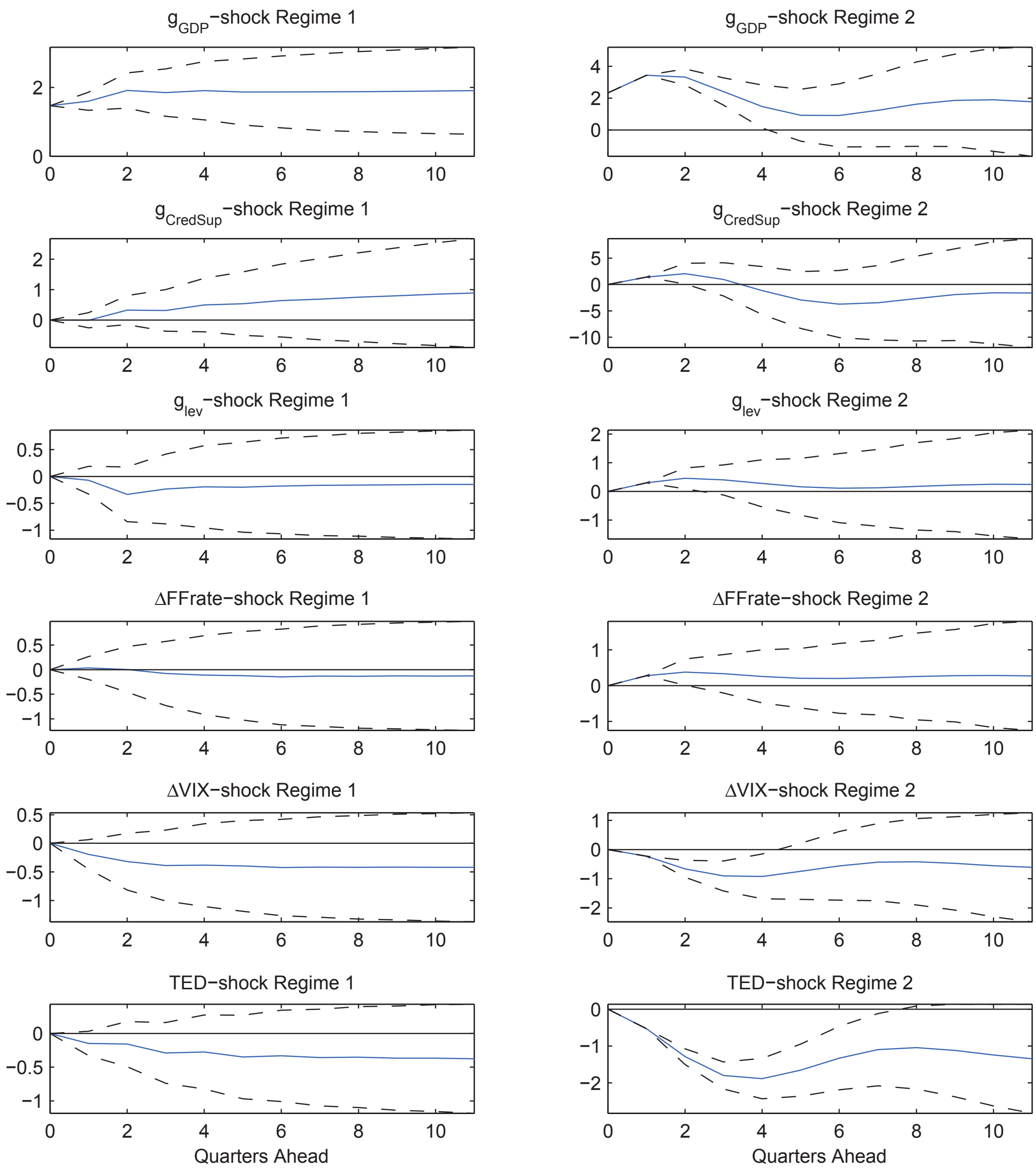
Figure 3.8 depicts the real effects of all the 6 different shocks for each regime separately. The effect of financial market conditions seems to dominate the other effects in regime 2. Note that, given the generally higher standard errors in regime 2, the absolute initial impacts of all shocks are considerably stronger in the ’bad’ regime. Even though the initial impacts of credit-supply and liquidity shocks are fairly large, they are short-lived.

[17] As explained in section 3.2.2, the linear impulse responses are calculated on the basis of the parameter estimates for each regime separately. A regime shift is not allowed, and hence they can be calculated in exactly the same way as in a linear VAR. The asymptotic confidence intervals are derived analogously.



The plots depict the linear cumulative Impulse Response Functions for each regime for a 1-std TED shock. The dashed lines denote the corresponding 90% asymptotic confidence intervals. g_{GDP}, $g_{CredSup}$ and g_{lev} are quarterly growth rates measured in % $p.a.$. The change in the Fed Funds rate $\Delta FFrate$ and the TED spread TED are measured in basis points p.a.. ΔVIX denotes the change in the VIX index.

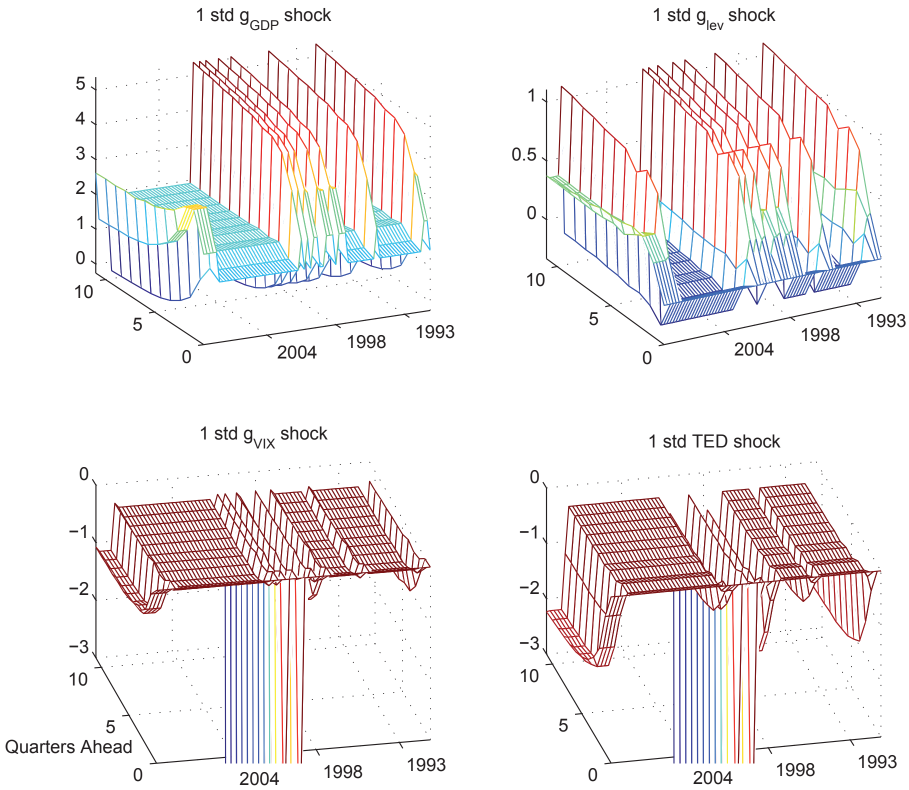
Figure 3.7: Linear Cumulative Impulse Response Functions for a 1-Std TED Shock



The plots depict the linear cumulative Impulse Response Functions of GDP growth for all types of shocks within the given regime. Each shock is of a 1-std size for the respective variable and regime. A 1-std shock in regime 2 is larger than a 1-std shock in regime 1, and consequently the observed initial absolute impacts are higher. The dashed lines denote the corresponding 90% asymptotic confidence intervals.

Figure 3.8: Linear Cumulative Impulse Response Functions for all Types of Shocks on GDP Growth

To illustrate the short and long-run impacts over time, Figure 3.9 contains the non-linear Impulse Response Functions, which allow for regime switches, as described in section 3.2.2.

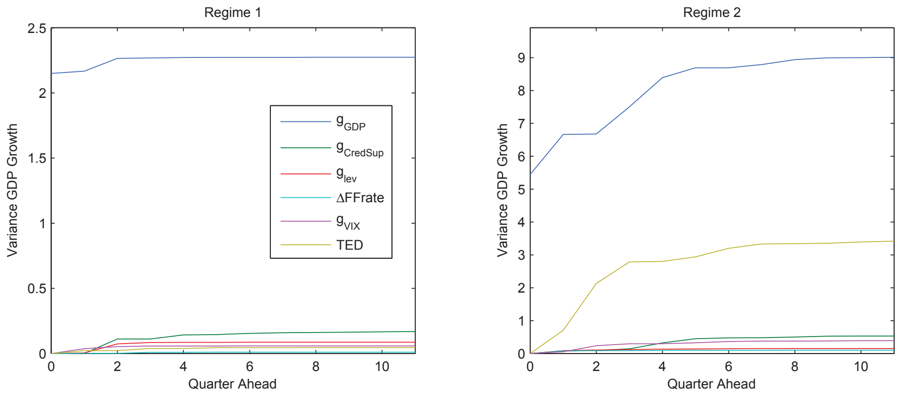


The surface plots show the non-linear Impulse Response Functions as described in section 3.2.2 for the respective shocks to GDP growth conditional on the time when the shocks hit.

Figure 3.9: Non-Linear Impulse Response Functions for Different Shocks on Output Growth

The graphs represent the cumulative impact of a 1-std deviation shock conditional on the time when the shock hits. Given the prevailing regime at this date, the 1-std shock can again have two different absolute values. The different impacts and responses over time and across regimes are very pronounced. In particular, it strengthens the evidence of a real effect of liquidity and financial market conditions in times of financial distress. The extreme negative long-run impacts of the g_{VIX} and TED shocks occur at the burst of the tech-bubble. Nonetheless, in the recent crisis at the end of the sample, the negative effects are also relatively strong. In distressed financial conditions, also the liquidity shocks have a stronger, though still small, impact on GDP growth.

To further investigate, which shocks are driving GDP growth, I conduct both a linear and a non-linear Variance Decomposition of GDP growth, which is explained in detail in the Appendix. Figure 3.10 provides the linear Variance Decomposition, taking the two regimes separately.

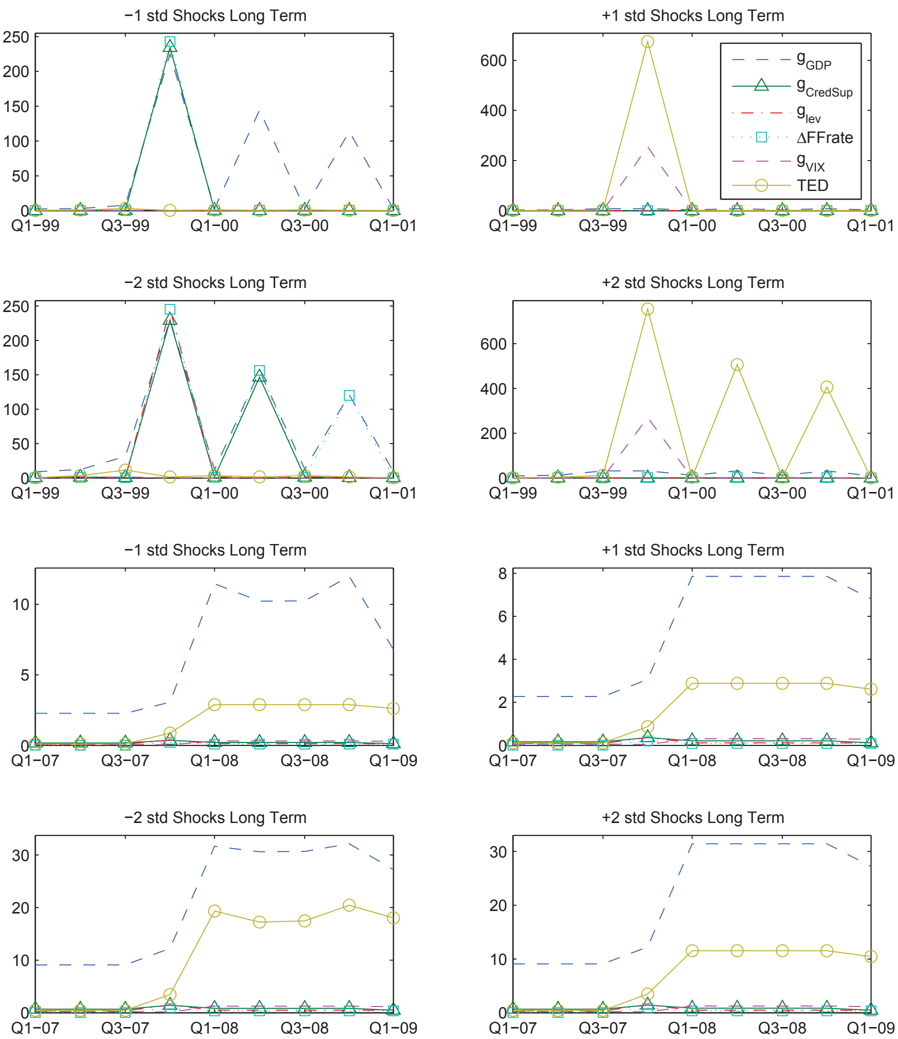


The two graphs show the linear variance decompositions for GDP growth for the respective regimes. The series plot the contribution of the respective shocks to the mean squared forecast error of GDP growth, with the forecast-horizon on the horizontal axis.

Figure 3.10: Contributions to Mean Squared Forecast Error of the Different Types of Shocks to Output

The forecast error of GDP growth in the first regime is, more or less, completely determined by its own shocks. In the "bad" regime, however, shocks to overall financial market conditions contribute noticeably to long run variance of GDP growth.

Figure 3.11 shows the non-linear variance decomposition for the period Q1 1999 until Q4 2000, which covers the tumultuous period of the 'dot-com bubble', and the analogous graphs for Q1 2007 until Q1 2009, in order to capture the recent financial crisis. The former period is very illustrative, as it exhibits several regime switches (see Figure 3.6). At each point in time, the contribution to the long-run variance of GDP growth is plotted for every shock. Regime switches can be easily identified as the periods where the variances, and therefore the variance contributions, are distinctively higher. Note that the variance contributions of the shocks are different depending on the size and direction of the shock. A negative shock is supposed to resemble the typical after-crisis situation.



The graphs depict the long-run variance contributions to GDP growth of the respective shocks for the 'dot-com bubble' and the 2007-2009 financial crisis for different sizes of initial shocks. The series are based on the non-linear variance decomposition as described in the Appendix.

Figure 3.11: Non-Linear Variance Decompositions for Output Growth

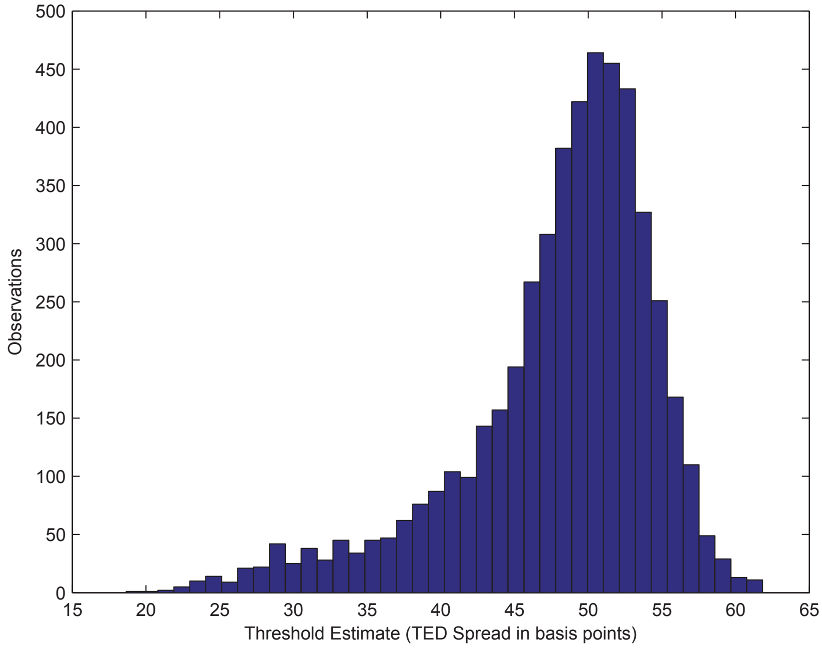
It implies not only a negative shock on output, credit supply and leverage, but also a negative shock to the TED spread, changes in the Fed Funds Rate and change in the VIX index. This is a situation, where financial markets are recovering, accompanied by expansionary monetary policy. In the 'dot-com bubble' period, the long-run variance of GDP growth in the recovery scenario is mainly driven by interest rate shocks and shocks to GDP growth itself. Credit Supply also seems to play a role, depending on the size of the negative shock. The situation for the end of the sample, however, is slightly different. The reason is that the TED spread is so high, that no real recovery scenario exists. A switch back to the favorable regime could only be achieved by a much larger negative shock. In this sense, the scenario with a negative shock is not fundamentally different from the scenario with the positive shock in the last 2 years of the sample, and consequently, the graphs look very much alike.

The scenario with positive shocks resembles a typical situation at the outbreak of a crisis, when economic growth is still solid, but financial market conditions are suddenly reversing. Banks, however, are still expanding their balance sheets and relaxing credit supply conditions. This is a scenario quite similar to the actual situation at the beginning of the recent financial crisis. The real effects of financial market conditions are again clearly visible. Besides output growth itself, the shocks to the TED spread, as well as the VIX index in the earlier period, are the main contributors to the variation in GDP growth; at the end of the sample period. This constitutes further evidence for the strong transmission mechanism of financial market conditions to the real economy in times of financial distress, which is absent in the 'normal' regime. Nevertheless, the shocks from the financial side can only explain around one-third of the long-run variance of GDP growth. At the end, more fundamental sources seem to drive economic growth, which may have to do with economic sentiment and expectations about future economic growth, reflected by the strong impact of the growth shocks themselves.

3.3.1 Robustness Issues

The Hansen (2002) test for the existence of a threshold clearly rejects the null-hypothesis of no threshold in the given specification, as reported in Table 3.2. Given the existence of a threshold, I perform an informal test[18] for the value of the threshold through a Monte-Carlo simulation. The simulation is done recursively, starting with the value of Y_t at $t = 1$ and then iterating forward using the Monte Carlo draws for the errors based on a Normal limiting distribution, with the variance equal to the variance of all estimated shocks, regardless of the regime. Note that the recursion is non-linear, since the appropriate parameters for the recursion depend on whether the TED spread is above the threshold, or not. The corresponding threshold is the original estimate of 49.9 basis points. Figure 3.12 shows the distribution of the threshold estimate, which exhibits a clear concentration around 50 basis points.

[18]A formal test for the value of the threshold, so far, is not available. This is due to the complexity of deriving a limiting distribution, since the distribution of the errors change with the threshold value. This is notwithstanding the problem of whether a threshold actually exists. Therefore, an informal test based on a Monte Carlo simulation seems a commensurate approximation to the testing problem.



The plotted distribution presents the outcome of 5000 Monte-Carlo simulations of equation (3.1). The simulations are based on the recursively generated values for the endogenous variables based on a Normal limiting distribution.

Figure 3.12: Distribution of the Threshold Estimate - Monte Carlo Simulation

Since the recursion generates regime-shifts in periods where no regime-shifts are observable in the original sample, the Monte-Carlo simulation is very likely to produce extreme deviations from the underlying data and therefore of the resulting estimates. Such a clear concentration of the simulated distribution around the actual estimate is arguably an indication of an exiguous variance of the threshold estimate.

Given the relatively precise threshold estimate, the results still depend on the proposed ad-hoc identification of the shocks, since a rotation of variables implies a different matrix of structural shocks P_1 (details are given in the Appendix). All possible orderings within the group of financial variables (g_{lev},$\Delta FFrate$, ΔVIX, TED) are tested and the results are robust to the rotations. If ΔVIX is moved further backwards in the ordering such that its shocks have no contemporaneous effects on the other variables, its long term impact on GDP growth and the TED spread diminishes. All other Impulse Responses, however, remain almost identical. Hence, the real effects of changes in volatility are possibly even smaller than in the baseline identification scheme. If a TED spread-shock is allowed to have a contemporaneous effect on g_{lev}, ΔVIX and $\Delta FFrate$, its real effects and variance contributions to GDP growth are even more pronounced. More realistic, however, seems an ordering where interest rate shocks have an immediate effect on expected volatility and financial market conditions and the Fed reacts to changes in financial markets in the following period.

Another meaningful, and more substantial, change in the identification scheme concerns credit supply conditions ($g_{CredSup}$). Arguably, credit supply growth could also be immediately affected by shocks on financial markets. As a robustness check, I choose $g_{CredSup}$ to be the last variable in the system. The corresponding cumulative Impulse Response Functions are plotted in Figures 3.13 and 3.14. For all the other variables, the responses are hardly different from the baseline model. The credit supply shock now has a slightly negative, albeit still small, impact on GDP growth. Accordingly, the linear variance decompositions exhibit no visible alteration and hence they are not shown. Also, the non-linear time-dependent variance decomposition for GDP growth, presented in Figure 3.15, is almost identical to the baseline ordering.

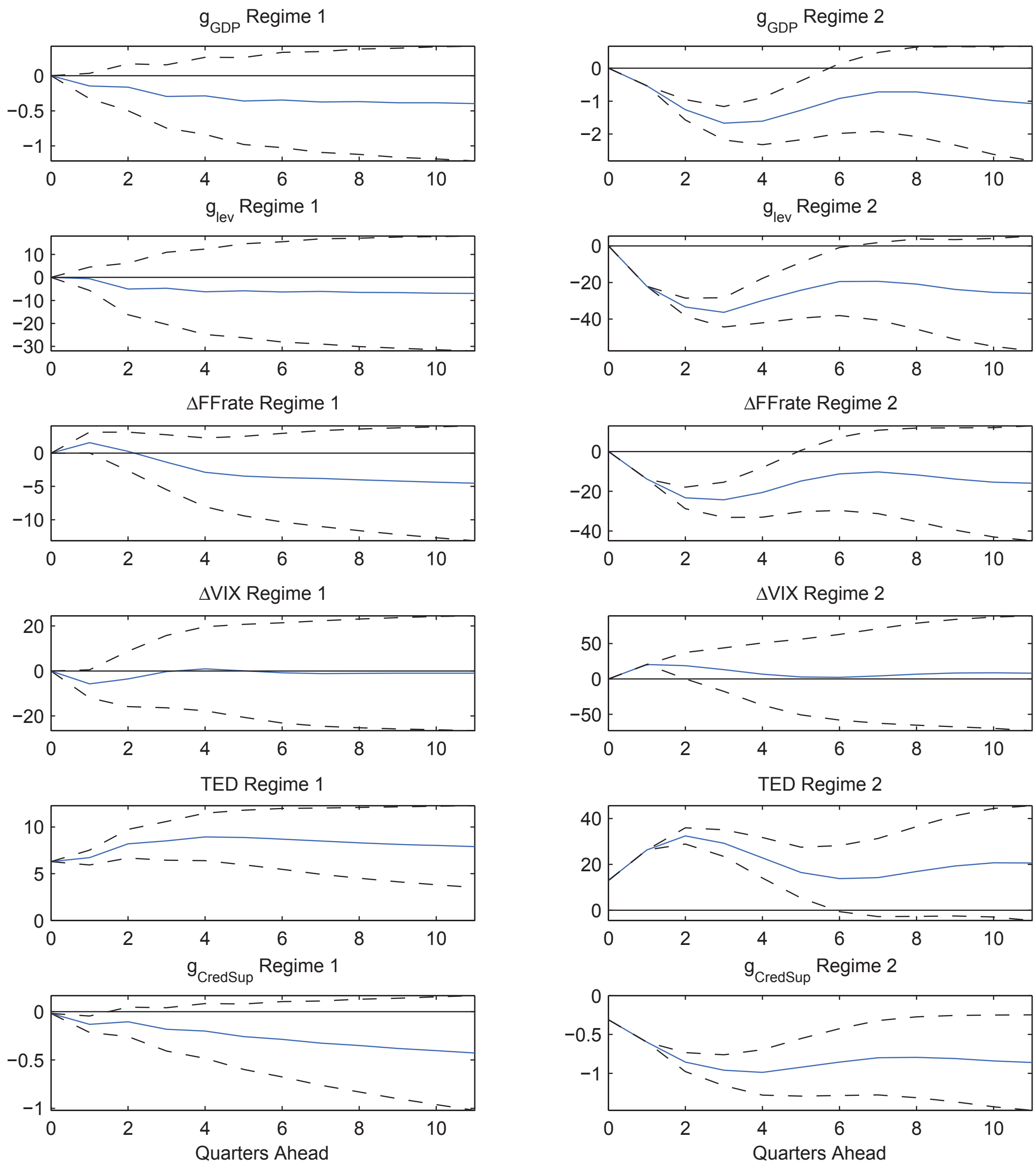
The two central results therefore seem to be independent of the orderings discussed above: (i) the transmission mechanism of financial market conditions to the real economy is stronger in situations of financial distress, whereas in normal times this effect is absent; and (ii) the real effects of financial market conditions are still not the dominant drivers of the real economy, which remain the output shocks themselves.

3.4 Conclusions

To capture non-linear and regime dependent feedback effects of liquidity and financial market conditions, this paper employs a Threshold VAR with the TED spread being the endogenous threshold variable, which was put forward as a measure for financial market conditions in general.

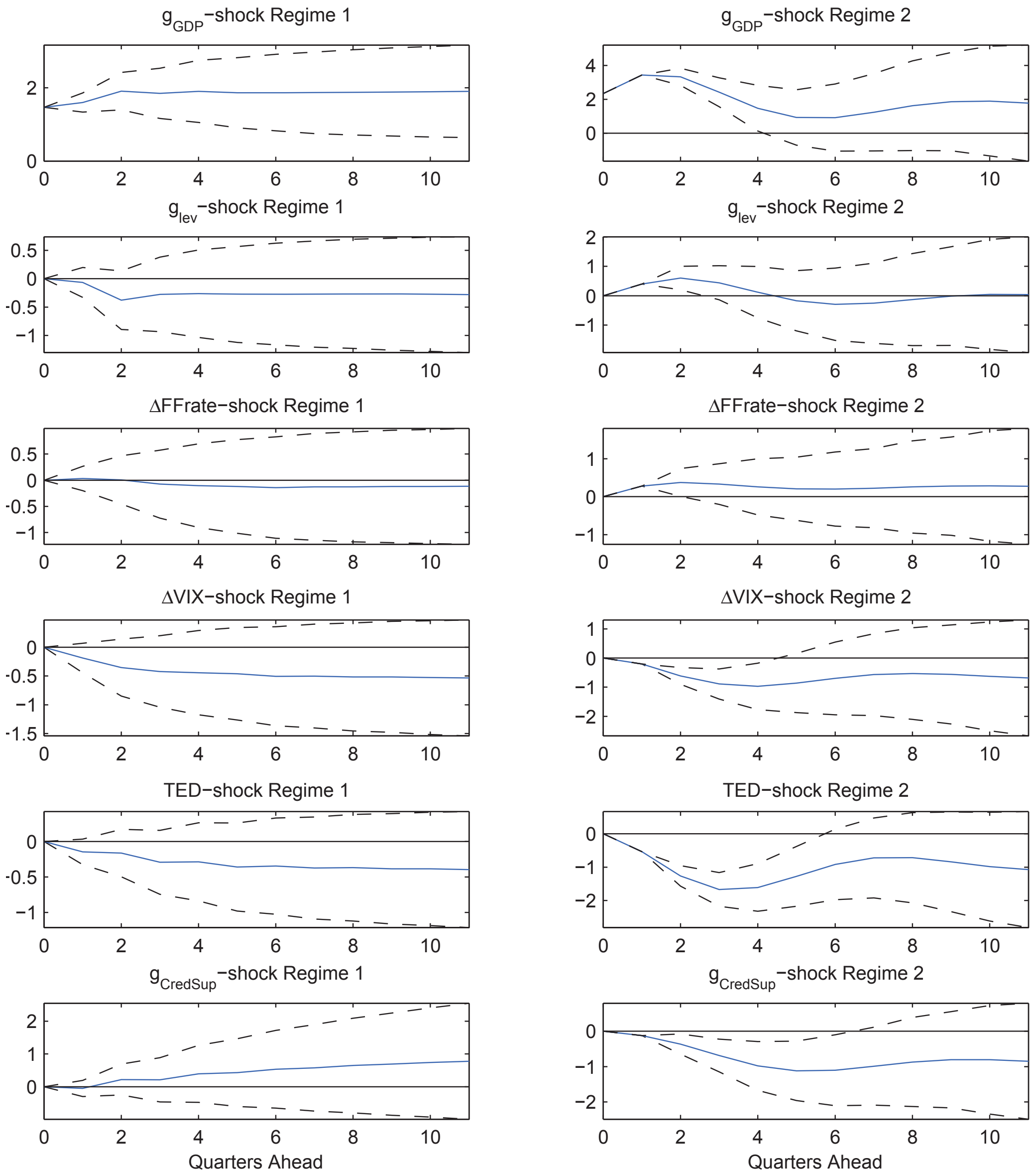
The model detected two regimes, which exhibit distinctively different transmission mechanisms in a system of GDP growth, proxied credit supply growth, leverage growth of commercial banks as a measure of funding liquidity, the Fed Funds Rate, the change in the VIX index as a proxy for expected volatility, and the TED spread. Regime 2, is identified by a TED spread above the estimated threshold of around 50 basis points and is supposed to indicate 'bad' or distressed financial conditions, whereas regime 1 reflects a 'normal' financial market environment.

Two main results can be carved out. Firstly, the transmission mechanism of financial market conditions to the real economy is much stronger in situations of financial distress, whereas in 'normal' times this effect is absent. Secondly, even though the real effects of financial market conditions are significant, they are not accountable for more than one third of the variation in GDP growth. Despite some evidence for a mutual feedback effect between financial market conditions and liquidity in regime 2, as suggested by Brunnermeier and Pedersen (2009), the feedback from liquidity shocks to financial market conditions and the real effects of liquidity shocks are small and short-lived. A non-linear Variance Decomposition of GDP growth suggests that during the dot-com bubble in 1999/2000 and the recent financial crisis 2007-2009 innovations in the TED spread are responsible for a significant part of the variation, given a shock which resembles an outbreak of a crisis scenario. In a recovery scenario, however, which in the underlying sample cannot be replicated for the recent financial crisis, interest rate shocks as well as credit supply shocks contribute strongly to the variation in output growth. This adds further evidence to the increasingly tighter links between financial market conditions and the real economy in times of financial crisis.



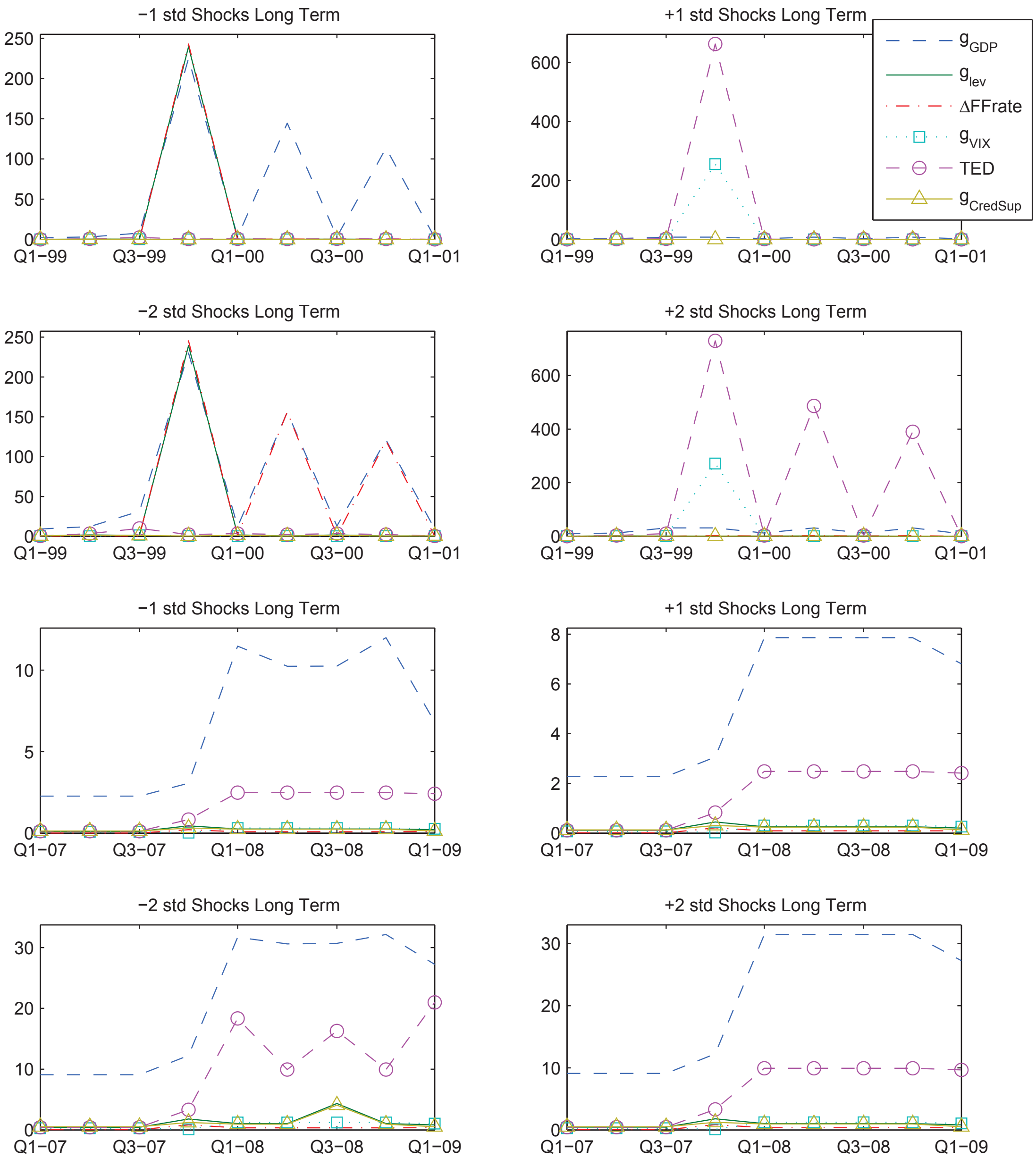
This Figure presents the analog to Figure 3.7 for the alternative identification scheme put forward in section 3.3.1. Plotted are the linear cumulative Impulse Response Functions for each regime for a 1-std TED shock. The dashed lines denote the corresponding 90% asymptotic confidence intervals. g_{GDP}, $g_{CredSup}$ and g_{lev} are quarterly growth rates measured in % *p.a.*. The change in the Fed Funds rate, $\Delta FFrate$, and the TED spread, TED, are measured in basis points p.a.. ΔVIX denotes the change in the VIX index.

Figure 3.13: Linear Cumulative Impulse Response Functions for a 1-Std TED Shock - Alternative Identification Scheme



This Figure presents the analog to Figure 3.8 for the alternative identification scheme put forward in section 3.3.1. Plotted are the linear cumulative Impulse Response Functions of GDP growth for all types of shocks within the given regime. Each shock is of a 1-std size for the respective variable and regime. A 1-std shock in regime 2 is larger than a 1-std shock in regime 1, and consequently the observed initial absolute impacts are higher. The dashed lines denote the corresponding 90% asymptotic confidence intervals.

Figure 3.14: Linear Cumulative Impulse Response Functions for all Types of Shocks on GDP Growth - Alternative Identification Scheme



This Figure presents the analog to Figure 3.11 for the alternative identification scheme put forward in section 3.3.1. The graphs depict the long-run variance contributions to GDP growth of the respective shocks for the 'dot-com bubble' and the 2007-2009 financial crisis for different sizes of initial shocks. The series are based on the non-linear variance decomposition as described in the Appendix.

Figure 3.15: Non-Linear Variance Decompositions for Output Growth - Alternative Identification Scheme

Appendix

Non-Linear Impulse Response Functions

The non-linear Impulse Response functions are defined as

$$IRF_{t+k|t}(v_t) = E\left[Y_{t+k}\left|Y_{t-1}, v_t\right.\right] - E\left[Y_{t+k}\left|Y_{t-1}\right.\right]$$

At time t, the economy can either be in the "good" regime or in the "bad" regime. In the dual regime setup given by equation (3.1), a "typical" one standard-deviation shock differs in magnitude between regimes. A 1-std deviation shock in the 'good' regime is typically smaller in absolute size than a 1 standard-deviation shock in the 'bad' regime across all types of shocks within the sample under consideration. For both regimes, the same contemporaneous identification scheme is applied. As both $\Omega_1$and Ω_2 are symmetric positive definite matrices, the lower triangular Choleski decomposition of the regime-dependent covariance matrices is given by

$$\Omega_1 = R_1 D_1 R_1' = R_1 \left(D_1\right)^{\frac{1}{2}} \left(D_1\right)^{\frac{1}{2}} R_1' = P_1 P_1'$$

$$\Omega_2 = R_2 D_2 R_2' = R_2 \left(D_2\right)^{\frac{1}{2}} \left(D_2\right)^{\frac{1}{2}} R_2' = P_2 P_2'$$

where D_1 and D_2 are matrices with only positive entries on the diagonal and 0 otherwise. The structural shocks are identified as

$$\begin{cases} u_t^1 \equiv \left(R_1\right)^{-1} \varepsilon_t^1 & \forall t : I\left(q_t \leq \gamma\right) \\ u_t^2 \equiv \left(R_2\right)^{-1} \varepsilon_t^2 & \forall t : I\left(q_t > \gamma\right) \end{cases}$$

The different Rs reflect the different transmission of shocks in each regime. By assumption

$$E\left[u_t^1 \left(u_t^1\right)'\right] = E\left[u_t^2 \left(u_t^2\right)'\right] = I$$

and

$$E\left[u_t^1 \left(u_t^2\right)'\right] = 0$$

The non-linear Impulse Response Functions can be calculated as follows:
Let the $j-th$ column of P_1 be $P_{j,1}$ and the $j-th$ column of P_2 be $P_{j,2}$. Furthermore, we have

$$IR_{t+k|t} = E\left[Y_{t+k}\left|Y_{t-1}, v_t\right.\right]$$

and

$$IR_{t+k|t-1} = E\left[Y_{t+k}\left|Y_{t-1}\right.\right]$$

The threshold element q in IR is denoted as IR^q. Then, do a recursion of the following type:

1. Choose the type j and size of the shock s in units of standard deviations plus the time period t in which the system is hit with the shock
2. Calculate $IR_{t|t}(j,s) = I(q_{t-1} \leq \hat{\gamma})\left[\hat{A}_1 Y_{t-1} + sP_{j,1}\right] + I(q_{t-1} > \hat{\gamma})\left[\hat{A}_2 Y_{t-1} + sP_{j,2}\right]$ and $IR_{t|t-1} = I(q_{t-1} \leq \hat{\gamma})\left[\hat{A}_1 Y_{t-1}\right] + I(q_t > \hat{\gamma})\left[\hat{A}_2 Y_{t-1}\right]$
3. Do a recursion for $k = 1, 2, ..., N$ with $IR_{t+k|t}(j,s) = I\left(IR^q_{t+k-1|t} \leq \hat{\gamma}\right)\left[A_1 IR_{t+k-1|t}\right] + I\left(IR^q_{t+k-1|t} > \hat{\gamma}\right)\left[A_2 IR_{t+k-1|t}\right]$ and the analogous for $IR_{t+k|t-1}$
4. $I\hat{R}F_{t+k|t}(j,s) = IR_{t+k|t}(j,s) - IR_{t+k|t-1}$ which is the $j-th$ column of $I\hat{R}F_{t+k|t}(s)$

At any k, $IR_{t+k|t}(j,s)$ and $IR_{t+k|t-1}$ can be in different regimes. This creates the non-linear behavior of the IRFs.

Non-Linear Variance Decompositions

The Mean Squared Error (MSE) of a k-period ahead forecast is

$$MSE_{t+k|t} = E_t\left[\left(Y_{t+k} - E_t\left[Y_{t+k}\right]\right)\left(Y_{t+k} - E_t\left[Y_{t+k}\right]\right)'\right] = \sum_k C_k \Omega_k C_k'$$

$$\sum_k C_k \Omega_k C_k' = \sum_k C_k P_k P_k' C_k' = \sum_j \left[\sum_k C_k P_{j,k} P_{j,k}' C_k'\right]$$

where C_k is the effect in period $t+k$ of a one standard-deviation (1-std) shock in period t divided by the corresponding standard deviation[19]. C_k can potentially be a product of both A_1 and A_2 elements. Each element of $\sum_j$ represents the variance contribution to the total variance of a shock of type j. The covariance matrix Ω_k is either equal to Ω_1 if $E_t\left[q_{t+k}\right] \leq \gamma$ or Ω_2 if $E_t\left[q_{t+k}\right] > \gamma$. The estimated MSE for a 1-std shock can in principal be expressed as a linear combination of the 1 standard-deviation estimated IRF. If, at some time $t+k$, the regime switches, a different covariance matrix must be employed. However, the non-linear IRFs include the covariance matrix at period $t-1$ and not $t+k$. If $I(q_{t-1} \leq \hat{\gamma}) \neq I\left(IR^q_{t+k|t} \leq \hat{\gamma}\right)$ for any k, then it is necessary to switch the estimated covariance matrix at least once. This can be done simply by a switching factor S.

[19] Note that this is not equivalent to the effect of a shock of absolute size 1, due to the non-linearities in the IRFs. Shocks of different sizes will create different contributions of each shock to the overall MSE.

The 1 standard deviation non-linear IRF is equivalent to

$$IRF_{t+k|t}(1-std) = C_k P_t$$

where P_t is either equal to P_1 if $q_t \leq \gamma$ or equal to P_2 otherwise. Given the Choleski factorization of Ω_1 and Ω_2,

$$P_k = P_t S_{r_t \to r_{t+k}}$$

where

$$\begin{cases} S_{r_t \to r_{t+k}} = P_1^{-1} P_2 & if\ I\left(q_{t-1} \leq \gamma\right) = I\ \wedge\ E_t\left[q_{t+k}\right] > \gamma \\ S_{r_t \to r_{t+k}} = I & if\ I\left(q_{t-1} \leq \gamma\right) = I\ \wedge\ E_t\left[q_{t+k}\right] \leq \gamma \\ S_{r_t \to r_{t+k}} = I & if\ I\left(q_{t-1} > \gamma\right) = I\ \wedge\ E_t\left[q_{t+k}\right] > \gamma \\ S_{r_t \to r_{t+k}} = P_2^{-1} P_1 & if\ I\left(q_{t-1} > \gamma\right) = I\ \wedge\ E_t\left[q_{t+k}\right] \leq \gamma \end{cases}$$

The switching factor can be expressed as

$$\begin{aligned} S_{2\to 1} &= P_1 \left(P_2\right)^{-1} \\ S_{1\to 2} &= P_2 \left(P_1\right)^{-1} \end{aligned}$$

The estimated MSE can now be efficiently calculated from the estimated 1-std non-linear IRFs. For each horizon $k = 0, 1, ..., K$

$$\begin{aligned} M\hat{S}E_{t+k|t} &= \sum_k I\hat{R}F_{t+k|t}\left(1-std\right) \hat{S}_{r_t \to r_{t+k}} \hat{S}'_{r_t \to r_{t+k}} I\hat{R}F_{t+k|t}\left(1-std\right)' \\ &= \sum_j \left[\sum_k I\hat{R}F_{j,t+k|t}\left(1-std\right) \hat{S}_{j,r_t \to r_{t+k}} \hat{S}'_{j,r_t \to r_{t+k}} I\hat{R}F_{j,t+k|t}\left(1-std\right)' \right] \end{aligned}$$

The estimated MSEs for shocks of other sizes can be obtained analogously by scaling P_1 and P_2 accordingly and by substituting the non-linear Impulse Response Functions $IRF_{t+k|t}$ with the corresponding values for the desired initial shock size.

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